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Productivity Convergence and Learning by Exporting, Firm-Level Evidence from Tunisia

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1. Introduction

Despite impressive economic growth, productivity in Tunisia has not increased as much as GDP in recent decades. This paper documents that only a few top-performing firms have increased their productivity; by and large, most manufacturing firms' productivity levels have remained stagnant. This finding might imply that Tunisia's recent GDP growth might be a one-off event rather than a sustainable trend, as the growth has been fuelled by an increase in factor inputs, rather than by an increase in productivity. Hence, increasing productivity is a key priority of economic and development policies in Tunisia.

Meanwhile, economic growth in Tunisia has coincided with economic openness, following its accession to the World Trade Organization (WTO) and its undertaking of the European Union Association Agreement. A key question arising from this phenomenon is how important export activities have been for productivity increases, thus bringing exporters closer to the technology frontier. In addition, it is important to understand which conditions affect the size of the benefits associated with exports.

This paper evaluates the role of technology distance and of exporting in productivity growth of manufacturing firms in Tunisia from 1997 to 2007. The purpose of this study is twofold.

First, I test whether less productive firms grow faster than more productive firms (whether there is convergence), both conditionally and unconditionally. There has been almost no evidence of unconditional convergence despite the prediction of existing theories. In addition, the previous convergence literature is largely cross-country analysis using industry-level data; firm-level evidence is rare even in developed countries and much rarer in developing countries, although a country's growth is ultimately driven by the growth of individual firms. If convergence is only conditional at the firm level, the evidence of convergence is not convincing because those conditions are ultimately factors in firms' productivity growth, and unconditional convergence is unlikely to exist at the industry or country level. However, if an unconditional convergence pattern is observed at the firm level, despite rare evidence at industry and country levels, research should focus on understanding the constraints that prevent firm-level unconditional convergence aggregating up to the industry level or country level. Therefore, I seek to fill the gaps in the growth literature by examining evidence of micro-level convergence.

Second, I examine whether exporting has a direct effect on productivity growth and whether the impact of exporting on productivity growth depends on the distance of the firm from the technology frontier. Whether more highly productive firms "self-select" into export markets, or whether exporting causes productivity growth through some form of "learning by exporting" (LBE) is an ongoing debate in trade and development economics literature. I link LBE literature to convergence literature by examining the importance of the interaction between exporting and the distance from the technological frontier in driving productivity growth, in addition to examining their separate effects. While there are numerous studies on the role of exports in technology transfer and productivity gains, its direct relation with convergence has been rarely explored. To my knowledge, this is the first or one of a few papers to examine the role of exporting as a driver of convergence.

I present an empirical framework in which technology distance and exports provide two sources of productivity growth. Following on the convergence literature, I consider productivity growth as a function of technology distance that is measured as the difference in total factor productivity (TFP) levels between a given firm and frontier firms with the highest productivity level within a disaggregated industry. In addition, following the literature on exports and productivity, I consider productivity growth as a function of firms' participation in exporting; however, going beyond the existing literature, I explore exports' effect on productivity with relation to technology distance. This framework allows me to test exports' effect on productivity while controlling for firms' previous productivity level relative to the technology frontier, which indirectly controls the potential selection issue of faster-growing firms becoming exporters.

The use of large numbers of firm-level data over a relatively long period of time (around 11,400 observations for TFP growth over the 11-year time period, maximum) enables me to generate statistically convincing results and to examine the disaggregated forces underlying firm-level productivity performance, such as technology distance and exports, while controlling for unobserved heterogeneity in the sources of productivity growth.

My main results are as follows:

First, there is strong evidence of unconditional convergence at the firm level, implying that firms far away from the technology frontier grow faster than firms close to the technology frontier, regardless of firm-specific characteristics, such as manager capability and know-how, which are often unobservable factors that influence firms' productivity growth. The estimated coefficient is approximately 6.7 percent, which implies that it takes less than eight years to eliminate 50 percent of the initial gap to the technology frontier.

Second, the evidence of convergence remains even stronger when I test the abovementioned empirical framework with firm-fixed effects and other control variables (conditional convergence). The estimated technology distance coefficients, which are the elasticity of technology distance related to productivity growth rate, are in the range of 12.0 to 14.5 percent. This means that a 1 percent greater distance from the technology frontier is associated with 12 percent higher growth from the initial growth rate, (for instance, if the initial growth rate were 2.00 percent per annum, a firm that is 1.00 percent further away from the technology distance would have 2.24 percent growth rate (2.00 × 1.12 percent = 2.24 percent), which is much larger than the previous findings from industry- and country-level studies.

Third, the fact that exporters exhibit higher productivity levels than nonexporters is explained by self-selection, but not because of LBE. While exporters show a higher TFP level than nonexporters, exports' role in determining rates of TFP growth is insignificant, and becomes negative when controlling for the previous year's technology distance.

Fourth, the farther a firm lies behind the frontier, the greater the potential for technologies to be transferred through exporting, and the higher the rate of productivity growth. My results show that an interaction term between exports and technology distance has a positive and significant effect on productivity growth. While exporters in general do not show faster productivity growth, probably because they are closer to the technology frontier, those far behind the frontier grow even faster when they are exporting.

Last, foreign direct investment (FDI) further facilitates technology spillovers, especially for exporters that are far behind the technology frontier, but innovation does not. Within the empirical framework, I explore the three-way interactions among previous year FDI (or innovation), exports, and technology distance. Although, in the case of FDI, there is a positive and significant effect of this three-way interaction term on productivity growth, for innovation, the three-way interaction produces a small but negative effect.

The results are robust for different specifications and econometric techniques applied to avoid potential measurement errors in export variables, collinearity between industry-invariant unobservables and firm-specific characteristics, and simultaneity between export and productivity. The results are also robust for different definitions of the technology frontier between domestic and international frontiers.

This paper is structured as follows: section 2 introduces the theoretical framework underpinning my main econometric equation and presents an overview of convergence and the LBE literature. Section 3 describes the data and provides a summary of stylized factors on firm productivity trends in Tunisia, using estimated TFP. Sections 4 and 5 present the empirical strategy, with associated concerns and solutions. Section 6 shows the econometric results and robustness checks. Section 7 is the conclusion.

2. Literature review

Technology distance and convergence — standing on the shoulders of giants[1]

Previous literature on convergence is based largely on neoclassical and endogenous growth theories and considers technology distance a source of convergence. In neoclassical growth theory, a diminishing rate of returns of factors is assumed; thus, countries that are poorer (and have less capital) have higher marginal productivity of capital. If countries are similar with respect to preferences and technology, then poor countries grow their income and productivity faster than rich countries. In an open global economy, factors — such as capital — can move from richer countries to poorer countries, where the return on factors is higher. Consequently, poorer countries grow their income and productivity even faster (Ramsey 1928; Solow 1956; Cass 1965; and Koopmans 1965).[2]

In a growth model with endogenous technological change, such as the Schumpeterian growth model, growth depends not only on innovation and technology, but also on a firm's ability to adopt existing innovation and technology. While frontier countries will benefit from introducing new technologies, follower countries gain more by adopting existing technologies, which is less costly and quicker than creating new technology. Therefore, distance from the technology frontier influences technology transfer from more advanced countries or firms to less advanced countries or firms. Countries further away from the frontier grow their productivity faster (Aghion et al. 2013; Acemoglu 2009; McMorrow et al. 2010).[3] Just as dwarfs standing on the shoulders of giants can see further, poorer countries that adopt existing technology grow faster.

Whether convergence is driven by higher return on factors or from adoption of existing technology — rather than creating a new one — previous growth theories predict that there is a force that promotes convergence of income and productivity.

1. This metaphor of dwarfs standing on the shoulders of giants was first used in 1678 by Isaac Newton to explain the uncovering of truth as a process that builds on previous discoveries.
2. In the neoclassical growth model, TFP is exogenous and corresponds to the Solow residual. In neoclassical growth models for closed economies, the per capita growth rate tends to be inversely related to the starting level of output per person. In particular, if countries are similar in respect to preferences and technology, then poor countries tend to grow faster than rich countries. Thus, there is a force that promotes convergence in levels of per capita income. The extended model for open economies provides higher convergence rate for poorer economies because of factors, such as capital, labor, and technology, which move from richer countries to poorer countries where the return on factors is higher (assuming diminishing rate of returns).
3. In the Schumpeterian model, entrepreneurs create innovation with the expectation of being rewarded with (monopoly) rents if their innovation is successful. However, these rents decrease when other firms imitate those innovations, and eventually disappear when new innovations occur that compete with the existing technologies and thereby drive them out of the market (creative destruction).

Despite the predictions of these theories, empirical findings do not appear to be consistent. The existing evidence is mixed and varies depending on the data and the country analyzed. However, evidence of convergence seems to be more obvious when using micro-level data. In this case, I review existing literature that has tested for productivity convergence across countries, industries, and firms. Summary of the literature reviewed appears in appendix A.

At the country level, there seems to be no correlation between technology distance and growth. For instance, when poor countries are taken as a whole in aggregate, there is no systematic tendency to grow faster than rich ones, (there is, in fact, even a negative convergence rate across countries). The existing evidence of convergence is regional convergence, meaning the productivity level becomes similar among narrowly selected developed economies, such as OECD countries or among the US states. Also, as opposed to predictions made by growth theories, the convergence that occurs is conditional. Evidence of convergence in a wider group of countries is found only when controlling for other factors — such as human capital and institutions— and country-specific circumstances (see, for instance, Barro and Sala-i-Martin 1990; Vandenbussche et al. 2006; Inklaar and Timmer 2009).

For industries, there is more evidence of convergence, as most convergence analysis has used industry-level data, but the convergence pattern is inconsistent and depends on the data used. Most literature has found large heterogeneity in convergence across industries. However, industries actually showing convergence over time vary depending on data. For instance, several studies on OECD countries have shown stronger convergence patterns across service sectors but not in manufacturing industries (Bernard and Jones 1996); while more recent industry-level studies on wider country-level coverage, including developing nations, found that manufacturing industries, but not services, exhibit strong unconditional convergence, regardless of geography, policies, or other country-level influences (Rodrik 2012). However, studies that include the agriculture sector tend to find that agriculture is lagging behind and not converging. These mixed results might be caused by the income levels of the analyzed countries, which could influence the economic structure of the countries and which sector becomes the major growth sector. In other words, the different patterns of results at both country and industry levels might be related to the relative position of the country or industry analyzed in the technology distance.

At the firm level, evidence of convergence is rare, due probably to the difficulty in obtaining firm-level data. However, the existing literature analyzing firm-level convergence confirms the findings of country- and industry-level studies in that there is large heterogeneity across industries in speed of convergence. For instance, high-tech industries, such as IT, show higher convergence rates than others (Nishimura et al. 2005 for Japanese firms).

Also, previous literature finds systematic variation of productivity growth according to the firms' distance to the technology frontier (see Aghion et al. 2005for UK firms).

In addition, the relative position of firms in technology advancement influences their relationship with exports, FDI, innovation, government policies, and productivity. Exports and FDI appear to improve firm productivity after controlling for the productivity convergence effect (see Kimura and Kiyota 2006 for Japanese firms). Also, being far from the frontier reduces firms' incentives to innovate. In other words, when firms are closer to the (domestic) technological frontier, competition has a stronger positive impact for innovation (see Aghion et al. 2005; Howitt and Prantl 2007 for UK firms). Moreover, the effect of government's policy on final output or productivity varies depending on a firm's distance to the technology frontier, by producing significant effects of the interaction term between specific policies and technology frontier variables (see Aghion et al. 2013 for summary of existing literature).

Moreover, firm-level convergence analysis tends to find that convergence is much faster among firms than among industries or countries. One reason might be that firm-level analysis sometimes uses different measures of convergence than industry- and country-level analysis. For instance, with firm-level data, the technology distance could be measured not only to the international technology frontier, but also to the domestic frontier (the firm with the highest productivity level in the country), unlike at the country and industry levels. The domestic technology frontier has been found to exert a stronger pull on domestic firms than does the international frontier, which might explain why firms far behind the technology frontier might not be able to learn from the global frontier, but would still benefit from domestic knowledge (Bartelsman et al. 2008).

Another reason might be that certain mechanisms that allocate resources from less productive to more productive firms are required for the faster firm-level convergence rate to be transferred to the industry-level. Industry productivity growth consists of productivity growth of existing firms, and the set of firms changes (productive firms enter and less productive firms exit), which reallocates resources across firms and industries, and thereby enhances aggregated productivity. Empirical studies document that the changes in the set of firms contribute to a significant portion of industry growth. For instance, in the case of Japanese service and manufacturing firms, convergence rate is higher when controlling for entry and exit dynamics (Nishimura et al. 2005). For the Taiwanese manufacturing sector, the productivity differential between entering and exiting firms accounts for as much as one-half of industry improvement in some industries (Aw et al. 2001).

This finding of faster convergence patterns in micro-level versus macro-level data is similar to the previous analysis demonstrating that inefficiency of the allocative process is also the reason industry-level convergence does not add up to aggregated convergence of the whole economy. For instance, lack of structural transformation, implying production resources from less productive industries move to more productive ones, is the reason there is greater evidence of industry-level convergence, but relatively less obvious results in cross-country convergence (Rodrik 2012). This inefficiency of the allocative process is also a key reason for the large differences in productivity across countries; facilitating allocative efficiency increases aggregate productivity (Bernard et al. 2007; Foster et al. 2008; Hsieh and Klenow, 2009).

However, evidence of existing firm-level convergence concerns mostly OECD countries; evidence from developing countries is rare or, to my knowledge, does not exist. As seen in country- and industry-level studies, convergence patterns may vary by income level; therefore, firm-level convergence in developing countries, like Tunisia, might be different from that in OECD countries.

Moreover, finding firm-level evidence of unconditional convergence has significant value for growth literature.

A country's growth consists of different factors, such as public spending and private sector growth. But the larger and more developed the country, the more limited the role of public spending, and growth is driven essentially by the private sector, which consists of individual firm growth. Thus, a country's growth is essentially the aggregated growth of individual firms in the country.

As mentioned previously, empirical evidence at the country level has not been consistent with the growth theory presumption of unconditional convergence, which refers to the income gap between two countries decreasing irrespective of their characteristics. When poor countries are taken as a whole, they do not show a systematic tendency to grow faster than rich ones over any reasonably long time horizon. Any convergence one finds is conditional; it depends on policies, institutions, and other country-specific circumstances. If growth rates are characterized only by conditional, economies will tend toward different levels of income in the long run. Also, if convergence is only conditional, the research should be focused on identifying conditions that make convergence feasible (Rodrik 2012).

At the firm level, unconditional convergence exists if firms far from the technology frontier tend to grow faster than those that are close, regardless of the firms' specific characteristics, such as their product, their size, or the skill level of their employees.

If convergence is conditional only at the firm-level, the existence of convergence is not convincing because particular conditions are ultimate factors of a firm's productivity growth, and, most importantly, unconditional convergence is unlikely to exist at the industry or country level, despite the prediction of exiting growth theories. However, if an unconditional convergence pattern is observed at the firm level, despite rare evidence of unconditional convergence at industry and country levels, research should focus on understanding the factors that prevent firm-level unconditional convergence aggregating up to the industry level or country level.

Therefore, evidence of unconditional convergence at the firm level can provide insightful micro-level evidence for growth literature, but gaps in the literature hinder examination of the unconditional firm-level convergence pattern.

Exports, knowledge transfer, and convergence

While the abovementioned studies largely examine whether there is convergence or not, they typically do not identify what drives the convergence, and specifically, what causes the technology spillover from more advanced economies to less advanced ones, and further, why convergence exists only in some industries.

For instance, even when there is unconditional convergence in manufacturing (Rodrik 2012), it is not clear what aspects of manufacturing drive convergence. One possible hypothesis involves the tradability of the manufactures. Exporters will learn from the international markets, and in turn generate knowledge spillover to nonexporters. In this case, tradable services should also demonstrate a similar pattern to manufacturing, and unconditional convergence would be associated with the tradable aspect, and not be limited to manufacturing. While previous firm-level studies have focused mainly on innovation and FDI as sources of technology transfer, exporting is another important source of technology transfer from the foreign knowledge base.

In fact, there are multiple channels that could generate learning by exporting (LBE), which describes the pattern of firms' productivity growth after entering a foreign market.

First, after gaining exposure to international buyers and partners, firms improve management practice and adopt advanced technology. This can be caused by foreign buyers providing technical assistance to exporters to improve production efficiency. Additionally, this could be led by partners in foreign-invested firms that are willing to transfer technology. Those exposures to international buyers and partners improve exporting firms' access to knowledge about more advanced production technologies (Yeaple 2005).

Second, exporters are exposed to more intense competition in international markets, which leads to opportunities and incentives to improve productivity. The increased market size also increases the expected benefits, therefore providing more incentive for firms to invest in technology. Indeed, the most productive firms adopt the most advanced technology, implying that the benefit of adopting new technology is proportional to revenue, while its cost is fixed. Also, larger markets and increased competition lead firms to invest in technology, but with lower markups (Aghion et al. 2006; Melitz and Ottaviano 2008; Bustos 2011).

Third, exporting may lead to faster learning about market opportunities for new products or about tailoring products to the specific needs of individual buyers. Exporting could also provide greater incentives for firms to upgrade production technologies since they must meet higher quality standards in international markets compared to domestic ones (Verhoogen 2007; Fafchamps et al. 2008).

Fourth, exporting could increase the demand for skilled labor and technology, thus enhancing innovation and productivity. Also, trade liberalization reduces tariffs on foreign intermediate inputs, which enhances product quality and productivity (Goldberg and Pavcnik 2007; Lileeva and Trefler 2010).

Last, exporting improves economies of scale in production and capacity utilization by expanding sales. This reduces a firm's vulnerability to occasional downturns in the domestic market, and results in productivity gains in new export entrants.

In fact, much of the literature has documented that exporters are systematically more productive than nonexporters. There is an export premium, meaning that exporters have higher productivity levels, employment, sales, wages, and capital intensity than nonexporters (see, for instance, Bernard and Jensen [1999] for US firms, and Clerides et al. [1998], among many others, for developing countries).

Some literature has also documented the positive correlation between exports and productivity growth, instead of productivity level. Cross-country studies document a positive relationship between trade and growth performance (Frankel and Romer 1999). There is unconditional convergence in export unit values. Once a country begins to export, it travels up the value chain in that product regardless of domestic policies or institutions. The lower the average unit value of a country's manufactured exports, the faster the country's subsequent growth, unconditionally (Hwang 2007).

However, the causal effect of exporting on productivity is unclear, since increases in productivity could also cause exports, or increases in both productivity and exports could be caused by other factors. In addition, if there is self-selection into exporting — in other words, only those firms that know they will have higher growth will export, since more productive firms can afford the sunk cost of export entry — the correlation of exporting and productivity growth cannot necessarily be interpreted as a causal relation.

In fact, the empirical evidence of LBE is somewhat mixed, while the evidence of self-selection is stronger (for instance, see Melitz 2003; Bernard and Jensen 1999) Some works find no evidence of productivity changes after exporting, and those that do, find that productivity changes differ in the time span and extent of the changes (Girma et al. 2004, Girma and Kneller 2005, Van Biesebroeck 2005; De Loecker 2007, Fatou and Choi 2013).[4] Therefore, whether more highly productive firms self-select into export markets, or whether exporting causes productivity growth through learning by exporting, is an ongoing debate in the trade and development economics literature.

One weakness of the previous studies on LBE is that they cannot distinguish clearly between effects of exporting and unobservable differences between exporting and nonexporting firms; thus causal effect requires careful interpretation. Since decisions to export and how much to export are the firm's endogenous choices, these empirical specifications fail to convincingly isolate the causal effect of exporting on productivity growth. Export status might be correlated with unobserved firm characteristics that directly influence both the level and growth rate of firm productivity.

To understand the causal effect between exporting and productivity growth, several techniques have been applied to control the simultaneous effect between productivity growth and exporting.[5] In my empirical analysis, I use these latest techniques to control for simultaneous effect between productivity growth and exporting, while controlling the relative productivity level using technology distance to the frontier. Further explanation on how I deal with this simultaneous issue is provided in the next section on empirical strategy.

4. The mentioned literature is well summarized in Fatou and Choi (2013)

5. One way to control for selection bias is to jointly estimate an equation for participation in export markets and by using full information maximum likelihood. However, this more structural approach does not solve the fundamental identification problem and may be sensitive to functional form assumption about the joint error distribution (Bigsten et al. 2004).Those works typically used two separate equations measuring exporting and self-selection separately, except for the endogenous productivity model, which is a function of exporting (for example, De Loecker 2013). Another approach is the use of matching estimators (for example, De Loecker 2007). However, matching cannot address bias associated with unobservable firm characteristics, although it can reduce bias caused by selection on observables.

Literature on Tunisia and neighboring countries

Only a few studies have analyzed productivity convergence in Tunisia or in its neighboring countries.

El Arbi Chaffai et al. (2009), using industry-level data, show that there has been TFP convergence in Tunisia and catch-up to OECD member countries in six manufacturing sectors from 1983 to 2002. However, the convergence rate varies across sectors. The technology gap with other OECD countries has been slightly reduced in the textiles and leather, building and ceramics, and, chemical industries, while the gap has increased in electronics and metallic products, and in food processing.

Guetat and Serranito (2007), using country-level data of per capital income, show convergence among 11 countries in the Middle East and North Africa (MENA), including Tunisia, from 1960 to 2000. They find that both absolute and conditional convergence is not rejected for the majority of the group. In other words, countries in MENA converge to their regional frontier or come to have similar productivity as their neighbors. However, they find that Tunisia is the only country that showed divergence from neighboring countries' productivity levels, probably because of the relatively different economic structure, and the better economic growth performance of Tunisia compared to other neighboring countries. This might imply that Tunisia showed convergence to the international, rather than to the regional frontier.

Meanwhile, Marouani and Mouelhi (2014), using industry-level data from 1983 to 2008, find that productivity increase within industry did not lead to structural change across industries. Although there are slight labor movement from agriculture and construction sector to services, particularly hotel and retail, those sectors that absorbed employment were not productive, and overall labor productivity has remained low over time.

These studies have tested the convergence pattern at the industry and country levels, but not at the firm level.[6] Therefore, I cannot directly compare my results with these studies; however, these studies provide valuable information related to productivity convergence in Tunisia.

6. Marouani and Mouelhi (2014) also used firm-level data but only for limited years and sectors.

3. Data and variables

The data used in this study come from the annual enterprise survey, Enquête Nationale sur Les Activités Économiques (ENAE), which is conducted by the Tunisian Institute of National Statistics (INS).

The data have been collected for approximately 2,300 firms surveyed each year since 1997. The survey coverage is extensive, as firms accounting for about 30 percent of total firms in Tunisia with six or more employees in each sector, excluding agriculture, are included in the sample. In each year, a sampling method was applied, taking into account stratifications by industry and company size in terms of actual employees. I have confirmed that the sample includes representative Tunisian firms, by comparing the key firm characteristics of the INS data with the aggregated information of firms listed by the Agence de la Promotion de l'Industrie (API).

The big drawback of the INS data is that the survey generates a repeated cross section, which is representative of the Tunisian economy, but creates difficulty in applying econometric techniques for panel data. However, since many firms appeared for at least two years, I construct a weakly balanced panel by linking firms through time. Therefore, econometric techniques for the panel data could be applied to the whole data set.

One of the benefits of the INS data is that the selection bias caused by the dynamics of firm entry and exit are a lesser concern than in a balanced panel, since the former includes representative samples, instead of a panel of firms that survives for consecutive years. In a balanced panel, there might be reasons some firms are repeated in surveys in select consecutive years; further, it would include neither firms new to the market nor those closing down.

Another benefit of the INS data is that they provide rich information on firm characteristics (industry, ownership), balance sheets (revenue, labor, tangible assets, expenditure on intermediate goods and on R&D), and production (export and production value), as well as other information that standard firm–level surveys would include, which permits an investigation of the research questions of this paper.

Using INS data, I estimated TFP using information of sales revenue, labor, intermediate input, and capital. I also estimated TFP growth, technology frontier, and distance to technology frontier (technology distance). How to estimate these variables is explained in the next section.

To understand export's effect on productivity, I use export amount variable to capture information about export intensity, and a dummy variable for export participation. To understand additional factors that might influence the relationship between export and productivity, I generate a dummy for foreign ownership (or FDI) and an innovation variable by using the sum of the investment amount in innovative activities — R&D investment, and paying royalties and receiving technical consulting services. Table 1.1 provides the list of key variables used for this paper.

Table 1.1 List of Variables

	Variable	Description	# of obs.	Mean	Std. dev.	Min.	Max.
Variables used to estimate TFP	ln_revenue_d	Log amount of sales revenue, deflated with output price index	16,464	13.91	1.65	6.17	21.50
	ln_labor	Log number of employees	16,472	3.98	1.23	0	8.48
	ln_interme~d	Log amount of intermediary material input, deflated with output price index	16,168	12.73	2.23	1.60	20.19
	ln_capital_d	Log amount of tangible capital assets beginning of year, deflated with capital price index	16,031	13.42	1.83	4.61	20.57
Key variables	TFP_GMM	TFP, as residual of production function using GMM	15,749	0.01	0.68	-4.83	6.38
	tfp_delta	TFP growth	11,428	-0.01	0.42	-5.62	5.04
	GAP1	Technology distance	15,749	2.36	1.15	0	9.32
	Exp	Dummy variable of export participation (exp = 1 if exporting)	16,473	0.51	0.50	0	1.00
	Expv	Log amount of export value, deflated	16,473	7.75	7.68	0	21.50
	FDI	Dummy variable of having foreign ownership (FDI = 1 if foreign ownership	16,473	0.27	0.44	0	1.00
	ln_n_innov	Log amount of investment in innovative activities, deflated	16,473	6.03	4.67	0	21.5
Previous year	LGAP1	Previous year technology distance	11,552	2.30	1.11	0	9.32
	Lexp	Previous year export status	11,996	0.52	0.50	0	1.00
	Lexpv	Previous year export amount	11,996	7.87	7.72	0	22.4
	LFDI	Previous year FDI status	16,473	0.18	0.38	0	1.00

TFP level and growth variables

Using INS data, I measure TFP for Tunisian manufacturing firms as the residual in a Cobb-Douglas production function, which gives output as a function of the inputs the firm employs and its productivity.

Denote firms by $i = 1,\ldots, N$, industries by $j = 1, \ldots, J$, and years by $t = 1, \ldots, T$. Output measured by sales revenue (Y) in each sector j, at time t is produced with labor (L), capital (K), and intermediary input (M). The empirical specification can be written as follows:

$$\ln Y_{ijt} = A_{ijt} + \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \delta_t + \delta_i + \xi_{ijt} \quad \text{(a)}$$

- Y_{ijt}: The output of firm i operating in sector j at time t, calculated by the sales revenue deflated by output deflators.
- K_{ijt}: The value of fixed assets at the beginning of the year, deflated by capital price index, from the National Account.
- L_{ijt}: Number of employees.
- M_{ijt}: The value of material inputs adjusted for changes in inventories, deflated by output deflator
- A_{ijt}: The Hicks neutral efficiency level of firm (TFP of firm) measured as the residual of the model/ stochastic error term
- δ_t: Time dummies for 1997–2007
- δ_i: Firm-fixed effect
- ξ_{ijt}: Idiosyncratic error, which varies across individual firms

I use the Producer Price Index (PPI) from the INS as output deflators. The INS provides the annual changes of producers' price for the six sub-industries within manufacturing during the period of data coverage. For the capital input, I have constructed the deflators from the Gross Fixed Capital Formation of the National Account. For material input, I am force to use the output deflators, since there is no annual input-output table to calculate the material deflators for each year.

TFP estimated from equation (a) in ordinary least square (OLS) or fixed effects (FE) might provide biased results if inputs are correlated with error term, A_{ijt} (simultaneous input selection bias). For instance, when there is exogenous price shock, if the materials are considered more easily adjustable than labor and capital, then material is more strongly correlated with the error term. Therefore, material is upwardly biased, and labor and capital are downwardly biased. To remove this simultaneous selection issue, previous researchers estimated TFP using the Generalized Method of Moments (GMM), which treats factor inputs as endogenous and uses its own lagged and differenced variable of outputs and inputs as instruments to provide a consistent estimate.

The INS data set has a relatively short time dimension (T = 11 maximum, after eliminating post-2008 information, although most firms do not show 11 years consecutively), and a large firm dimension (more than 16,000 firm observations), which is another reason to use GMM.

Thus, I use GMM to estimate the above specification, specifically, non-dynamic system GMM with lag (2 3) for instruments. I treat all current year factor inputs — labor, capital, and material — as endogenous, and use previous two- and three-year information as instruments for all endogenous inputs. A dynamic model, which has a lag-dependent variable and lag factor inputs as additional regressors, requires one additional lag in instruments, which significantly reduces the number of observations, with the weakly balanced INS data. Therefore, I use a nondynamic equation. Likewise, further lags in instruments reduce the number of observations significantly; therefore, I use 2 and 3 lags in instruments.

Also, I measure TFP separately at the two-digit industry level in manufacturing, which is from NACE 15-37, to allow factor input shares to vary across industries. While some industries, such as automobile and chemical industries, are more capital intensive; others, such as textile or printing, are more labor intensive. Therefore, assuming the same factor inputs across different industries could cause bias in TFP estimation. More detail on TFP estimation and GMM is provided in appendix B.[7]

In 2008, the INS questionnaire changed, and dropped questions about exports. Therefore, I use the data from 1997 to 2007. Also, since the focus of this paper is the manufacturing sector, I limit my data to manufacturing firms, which belong to NACE code 15-36. After dropping those observations with missing values in key variables, such as revenue and employment, I obtain about 15,800 TFP from approximately 16,470 firm observations.

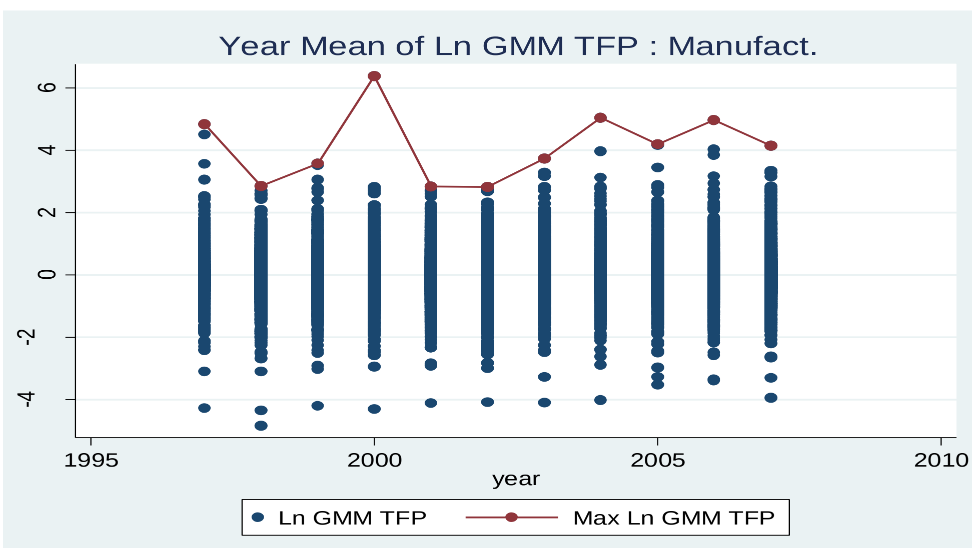
7. It is worth mentioning that there are also other ways of measuring productivity that have been used in previous convergence literature, such as index numbers, as shown by Bernard and Jones (1996). However, I have used TFP instead of index numbers because, in my view, there are several advantages of using TFP instead of using index numbers, especially on firm-level data. Index numbers require an assumption on the input share or use the industry average input share across all firms, and, therefore, do not reflect firm-specific information and could thus lead to bias. Also, using index numbers may not control for simultaneous bias, which could be caused by not only input influencing output, but also by output influencing input decisions.

The number of observations further dropped to around 9,400 when I calculated TFP growth, since two consecutive years of TFP information is required in the data. To increase the number of observations, I utilized additional information in the INS survey, which also asked firms for their previous-year revenue, employment, capital, and material cost. This effort generated previous-year TFP information for approximately an additional 400 firms.

Further, to increase the number of observations, I measured the TFP growth with the current year TFP and with available previous years, but the most recent if several previous-year observations exist. Measuring TFP growth in this way allowed me to use information of all firms in the data set that appeared at least twice during the period, which is true of the majority of observations. This endeavor generated previous-year TFP information for an additional 1,600 firms. Through these efforts I have obtained approximately 11,400 observations for TFP growth, which is about 70 percent of observations.

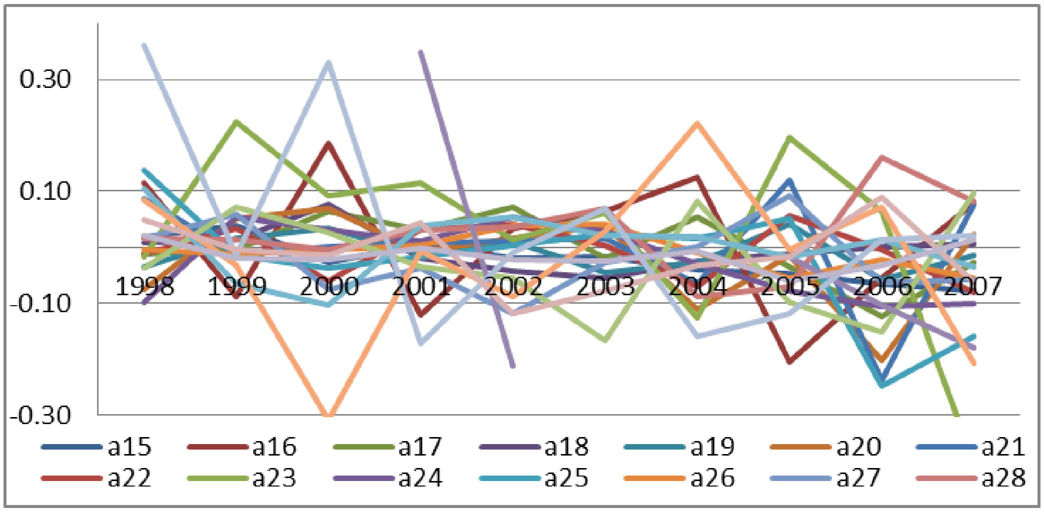
Using close to 70 percent of the firms in the data reduce potential selection bias if there is a reason those firms appear in the data at least twice. Moreover, the number of observations is large enough to produce statistically convincing results for both beta (β) and sigma (σ) convergence. Graphs 1.1 and 1.2 show the TFP level and growth for manufacturing firms in the INS data.

Graph 1.1 TFP Level for Tunisian Manufacturing Firms over Time



Graph 1.1 shows the TFP level for Tunisian manufacturing firms from 1997 to 2007. Most firms have TFP level between -log 2 and log 2 during this time. While the exact pattern is unclear from this chart, the differences in TFP among firms seem to be slightly reduced over time.

Graph 1.2 TFP Growth, Industry Average over Time



Note: The TFP growth is measured as; $\log(\text{TFP}_{ijt}) - \log(\text{TFP}_{ijt-1})$. I have dropped a35 to make the graph easier to read since the TFP growth rate was below -0.3 or above 0.4 in those industries. The index of each industry is provided in table 1.2 below.

Graph 1.2 shows average TFP growth rates over time by two-digit–level industry. While growth rate vary a lot by years and by industries, the average TFP growth rate is in the range between -0.2 and 0.2 for most industries and most years, except for a17 in years 1999 and 2007, a18 in year 2001, a32 in year 2000, and a33 in years 1998 and 2000.

Tables B.1 and B.2 in appendix B show the average TFP growth rates and their standard deviation (SD) by industry and by year. TFP growth has been negligible and close to zero for most industries, and the variance across years has also been very small.

Technology frontier and technology distance variables

Using the estimated TFP, I identified a technology frontier firm (TFP_{Fjt}), defined as a firm that has the highest TFP level within industry *j* and year *t* in Tunisia, followed by Bartelsman et al. (2008).

Unlike industry-level studies, firm-level studies are unique in allowing measurement of the domestic technology distance to the domestic technology frontier firm, defined as the firm that has the highest TFP level within the industry *j* and year *t.* The pattern of convergence to domestic technology frontier could be different from convergence to international technology frontier. Specifically, firms far behind the technological frontier might not be able to learn from the global frontier, but do still benefit from domestic knowledge

(Bartelsman et al. 2008).[8] Therefore, I use domestic technology frontier in my analysis as firms in developing countries, such as Tunisia, where markets are less integrated with international markets, are more likely to converge to the domestic frontier.

Then, I estimate the distance to technology frontier (technology distance) as a difference of log productivity level of the technology frontier firm (TFP_{Fjt}) and a firm's TFP level (TFP_{ijt}).

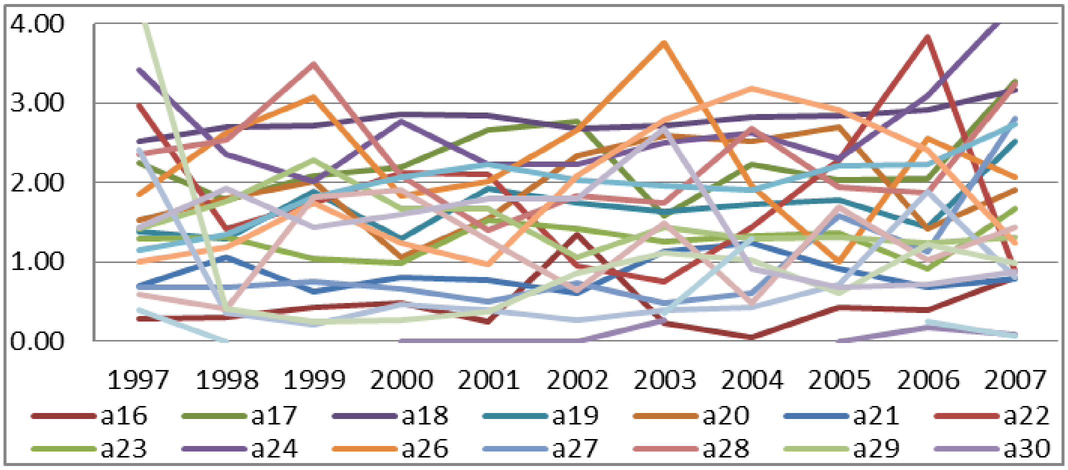
- Technology frontier (TFP_{Fjt}) : A firm that has the highest TFP level in sector *j,* at time *t*
- Technology distance: $\log\left(TFP_{Fjt}\right) - \log\left(TFP_{ijt}\right)$, which is equal to $\log\left(TFP_{Fjt}/TFP_{ijt}\right)$

It is worth mentioning that there are also other ways to measure technology frontier, such as stochastic frontier model (Aigner et al. 1977). In this model, frontier is identified as firms' profit maximization (or cost minimization), and technology efficiency is the ratio of observed output to maximum feasible output. While the frontier in stochastic frontier analysis uses a "half-normal" distributional assumption as the basis for measuring distance from the frontier, the technology frontier I use is a fitted full normal distribution of firms behind the frontier. Under this distributional assumption, my technology frontiers are mostly within the 99th percentile, depending on the number of observations within the industry *i* and year *t.* Thus, the median firm will be three standard deviations (SDs) below that level. For instance, in the textile industry in year 1997, there are 133 firm observations, and the technology frontier firm has a TFP level of log 2.24, while the mean TFP level of textile firms in year 1997 is close to zero (-0.02).

Graphs 1.3 and 1.4 show technology distance and its standard deviation over time.

Graph 1.3 Technology Distance (TFP GAP) over Time, by Industry

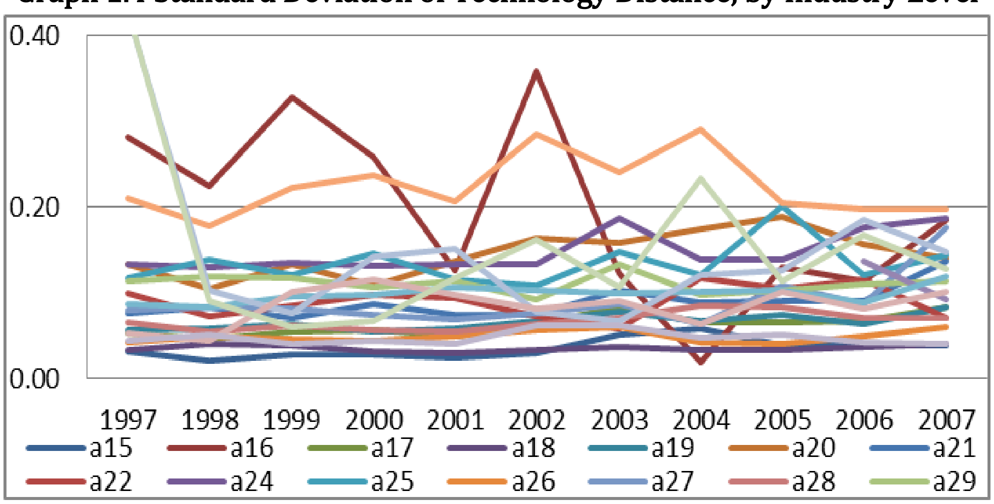
8. Bartelsman et al. (2008) found that the convergence patterns of UK firms to global and national frontiers are quite different. The national frontier exerts a stronger pull on domestic firms than does the global frontier. The pull from the global frontier falls with technological distance, while the pull from the national frontier does not.



Note: I deleted the line for a15 and a25 industries to make the graph easier to read since the technology gaps in both industries were over 4. The index of each industry is provided in table 1.2.

Graph 1.3 shows large heterogeneity in technology distance across industries. The technology distance is in the range of 0 and 3 in most industries. This implies that firm's TFP can be very similar to the technology frontier (if $\mathrm{TFP}_{\mathrm{Fjt}} = \mathrm{TFP}_{\mathrm{ijt}}$, technology Distance is log 1, which is 0), but can also be more than 20 times smaller than the technology frontier (ln 20 is almost 3), which is quite large. Also, the technology distance has increased in some industries, but not in others.

Graph 1.4 Standard Deviation of Technology Distance, by Industry Level



Note: I deleted a23 since its SDs are higher than 0.6 in some years, and these seem to be outliers.

Graph 1.4 shows the standard deviation of the TFP gap in each industry by year, which is the measure of sigma convergence widely used in previous literature. While in most industries the standard deviation seems to be slightly increased, in some industries, such as a16, a26, and a29, it was much reduced. However, in most industries, the standard deviation of technology distance has been sustained in the range of 0.03 to 0.15. This implies that while the top performer has grown much faster, the distance of other firms from this top performer has not changed much. Again, there is large heterogeneity in sigma convergence patterns across industries. Table B.3 in appendix B shows the actual standard deviation of the technology gap variable by industry and year.

It is important to note that the frontier firm of one given year is not necessarily the frontier firm in another year. As mentioned above, the INS data set is a survey of a representative sample of approximately 30 percent of all Tunisian firms; therefore, the firms selected in the survey are different each year (a weakly balanced panel). Also, firms can move up or down in their productivity level, or even exit from the market, while new firms that enter the market can be included in the data set. Therefore, the above firms show the overall trend of the sub-industries in the manufacturing sector, and not the trend for a group of specific firms.

Table 1.2 shows the average TFP level, average TFP growth rate, and the number of frontier firms by industry, which shows the weakly balanced characteristic of the INS data. For instance, in food industries, although there are 2,030 observations, the number of firms is 597, meaning firms were repeated on average less than four times during a period of 11 years. Average TFP level from 1997–2009 is close to zero, but growth rate is close to −2 percent. In the case of food industry (NACE 15) eight firms have been frontier firms out of 11 years, meaning the same firms repeatedly become frontier firms only for three years, or two firms are at the frontier for two years and all the rest at the frontier only once.

Table 1.2 TFP, TFP Growth, and Frontier Firms, by Industry

NACE code	Description	# of obs.	# of firms	Mean TFP	Mean TFP growth	# of frontier firms
15	Food industries	2,030	597	0.00	-0.02	8
16	Tobacco industry	46	7	0.26	0.01	3
17	Textile industry	1,246	354	0.01	0.00	11
18	Clothing and furs industry	4,947	1,263	0.03	-0.01	4
19	Leather and footwear industry	965	257	-0.03	-0.01	8
20	Wood working, wood manufacturing	275	98	-0.22	-0.01	5
21	Paper and carton industry	254	62	0.27	0.01	7
22	Editing, printing, reproduction	430	133	0.05	0.00	7
23	Coke, refining, nuclear industries	44	7	-0.42	0.02	5
24	Chemical industry	787	180	0.03	-0.02	8
25	Industrial rubber and plastics	637	172	-0.16	-0.02	9
26	Manufacture of other nonmetallic mineral	1,256	328	-0.01	-0.01	8
27	Metallurgy	235	52	-0.05	-0.02	6
28	Metalworking	871	275	0.04	0.02	10

29	Manufacture of machinery and equipment	382	100	0.05	-0.02	6
30	Manufacture of office machinery and computer equipment	11	5	0.82	-0.06	2
31	Manufacture of machinery and electrical appliances	598	161	-0.07	0.00	7
32	Manufacture of radios, TVs, and communication equipment	167	50	0.46	-0.02	7
33	Manufacture of medical, optical, and watch devices	101	30	-0.05	0.01	9
34	Automotive	253	69	-0.08	-0.01	8
35	Manufacture of other transport equipment	131	43	-0.09	-0.06	8
36	Manufacture of furniture; various industries	791	224	0.02	-0.01	6

4. Empirical strategy

Previous literature has typically measured convergence in two ways. First, it has compared the speed of growth of the poor and the rich (so called, β-convergence). The idea is that if a poor country tends to grow faster than a rich one, the poor country is able to catch up with the rich one. Second, the literature measures cross-sectional dispersion (σ-convergence). Convergence occurs in this case if dispersion, measured by the standard deviation of the income or relative productivity across a group of countries or industries, declines over time. As mentioned above, there is no clear pattern of σ-convergence in Tunisian manufacturing firms (for more details, see table B.3 in appendix B).[9]

The empirical model that I present aims to test β-convergence patterns. Previous studies have tested the existence of β-convergence, mostly by regressing productivity growth on two key explanatory variables. The first is an estimate of productivity growth at the frontier, which captures the link to productivity growth in the "catching-up" country. The second is a measure of technology distance, which is the productivity of the poor relative to the productivity of the technologically advanced. This technology distance variable captures the extent to which productivity growth in a specific country can be explained by the adoption of more efficient existing technologies in a Schumpeterian framework. Those empirical models aim to capture the link between productivity growth of the poor and the extent of knowledge spillover from the most technologically advanced (Barro and Sala-i-Martin 1990[10]; Bernard and Jones 1996; Nishmura et al. 2005; Griffith et al. 2008; McMorrow et al. 2010).

9. β-convergence works toward convergence of σ-type convergence; however, it does not guarantee σ-convergence, especially when growth rates are driven not just by the forces of convergence but also by other external shocks, such as economic crises, which are new disturbances that tend to increase dispersion (Barro and Sala-i-Martin 1990).

10. In case of the growth model of Barro and Sala-i-Martin (1990), convergence exists if the coefficient gap variable (β) is greater than 0. If β = 0.03 per year, (it takes about 12 years to eliminate 50 percent of the initial gap).

Following on the previous studies, I test the existence of β-convergence by regressing a firm's productivity growth on its relative technology distance, which is its previous year TFP relative to the above-identified technology frontier firm's TFP, as seen in equation (1.1). I estimate equation (1.1) with OLS without any control variables. Therefore, the coefficient, η_1, describes the existence of unconditional convergence: the further away from the technological frontier, the higher the potential to adopt more efficient and available technologies, and consequently the faster the productivity growth, regardless of a firm's specific characteristics.

$$\Delta \ln A_{ijt} = \eta_1 \ln \left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \varepsilon_{ijt} \tag{1.1}$$

Then, I measure productivity growth as a function of previous-year export status, as seen in equation (1.2), following on previous empirical literature on exports and productivity. For instance, Castellani (2002), Baldwin and Gu (2004), and De Loecker (2013) produce empirical models in which productivity is dependent on previous export experience, based on the assumption that the current status of exporting influences future productivity, and find exporting has a positive effect on productivity.

$$\Delta \ln A_{ijt} = \eta_2 \, Export_{ijt-1} + \gamma \, X_{ijt-1} + U_{ijt} \qquad (1.2^{11})$$

- η_2 is the export effect on productivity growth.
- $Export_{ijt-1}$ is a dummy variable of previous-year export status.
- X_{ijt-1} is a vector of control variables, which includes innovation and FDI.
- U_{ijt} is a stochastic error.

I control for unobserved heterogeneity, which is correlated with the explanatory variables, by allowing the error term (U_{ijt}) to include a firm-specific fixed effect (α_i). I allow the error term (U_{ijt}) to include a full set of year dummies (α_t) and a full set of industry dummies (α_j). Since I have already controlled firm, industry, and time effects in computing the dependent variables, I expect that the coefficient of α_t and α_j would not be significant; however, I included them because there may also be a specific trend by common macroeconomic shocks and by industry that affects the relationship between export and TFP growth. Because some firms have changed their industry over time, industry dummies and firm-

11. Previous empirical literature on productivity convergence typically used either output/ income growth or productivity growth as a dependent variable. Given that the output growth consists of factor input growth and productivity growth, using output growth as a dependent variable while controlling factor inputs as independent variables is essentially the same as using productivity as a dependent variable.

fixed effects are not perfectly correlated, which allows me to use both. Some industries, in which industry dummies are perfectly correlated with firm-fixed effects, are automatically deleted in stata during the regression analysis. ε_{ijt} is a serially uncorrelated error.

$$U_{ijt} = \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt}$$

I link equations (1.1) and (1.2) above, and augment them by adding an interaction term between the previous export status and technology distance, based on the assumption that the learning by exporting effect depends on the level of technology distance, and export status plays a role in technology transfer.

$$\Delta \ln A_{ijt} = \beta_a \text{Export}_{ijt-1} + \beta_b \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_c \text{Export}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + X_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \quad (1.3)$$

- TFP_{Fjt}: The most productive firm (technology frontier = *F*) in sector *j,* at time *t*

In equation (1.3), β_a measures whether exporting has a positive effect on productivity growth. β_b measures the role of technology transfer in productivity growth. If firms behind the technology frontier grow faster than firms close to the technology frontier, β_b would be positive, (β_b is also the elasticity of productivity increase with respect to distance from the technology frontier). Lastly, β_c captures the variation of learning effects from exporting on a firm's relative productivity level and whether export plays a role in the relationship between technology distance and productivity growth. I expect that the further away a firm is from the technology frontier, the higher the learning might be; therefore, $\beta_c > 0$.

Thus, this specification in equation (1.3) is related to both convergence and to learning by exporting literature [12]. This specification has particular implications for standard measures of β-convergence — whether poor economies tend to grow faster than rich ones. Moreover, this specification allows me to test the effects of exports on productivity increases while controlling for firms' initial productivity levels, relative to the technology frontier — which indirectly controls potential self-selection of whether more productive firms become exporters — in testing the LBE effect.

This specification is similar to previous convergence literature, such as Griffith et al. (2004), in the sense that it is testing the relative productivity level and other factors on

12. As shown in literature review, evidence of convergence is typically tested by productivity growth (or output growth) as a function of initial productivity level or relative productivity (technology transfer/ distance).Taking a simple version of equation (1.3), writing TFP as A throughout and dropping extraneous terms, including export status and interaction terms. Equation (1.3) now becomes $\Delta \ln A_{ijt} = \beta \ln\left(\frac{A^F}{A_{ij}}\right)_{t-1} + \varepsilon_{ijt}$, which is typical convergence model.

productivity growth. However, while their focus was the relationship between R&D and productivity growth, my interest is in understanding exports' effect on productivity growth. Also, while they used industry-level data to test the existence of convergence across countries, I test firm-level convergence within industries in Tunisia.

Moderating effects of FDI and innovation

Other factors, such as foreign ownership (FDI) and innovation, may also influence exports' effect on productivity. Those factors might affect TFP growth directly, or via their interaction with the explanatory factors in the baseline specification. For instance, if foreign ownership and innovation facilitate learning from technologically more advanced firms, the export's effect on productivity growth would also be affected by those variables. Therefore, in the baseline specification of regression 3, I include those factors as control variables. In addition, I test the additional interaction of these factors with the interaction term for export and technology gap.

FDI has been widely recognized as a productivity source, since foreign investors' knowledge is transferred or spills over to domestic partners, competitors, suppliers, and customers via management skill and know-how. Multinationals are among the most technologically advanced firms, spending large amounts on R&D and using good managerial practices. Therefore, FDI as a bundle of technological and managerial knowledge has been regarded as a major vehicle for the transfer of advanced foreign technology to developing countries (Fu et al. 2012). Also, having foreign ownership can influence a firm's export participation. FDI firms are more likely to be exporters than local firms, which suggests that FDI is an important vehicle for trade, and that additional productivity gains can be reaped through trade (Javorcik et al. 2011).

Meanwhile, previous findings also suggest that benefits from FDI depend on absorptive capacity of local firms. For instance, spillover from FDI firms was observed in upstream sectors in Lithuania and in China (Javorcik 2004; Wei and Liu 2006; Du et al. 2011), in downstream sectors (Javorcik and Spatareanu 2011; Du et al. 2011), and horizontally (Damijan et al. 2013; Du et al. 2011).[13] However, there is a minimum absorptive capacity threshold level below which productivity spillovers from FDI are negligible or even negative (Smeets 2008). The magnitude and direction of the spillover effects from FDI

13. One would assume that FDI spillovers affect exit only in FDI recipients in developing countries since foreign investors from rich countries might bring more advanced technology to developing countries. However, these observations also hold for investors from developed economies. For instance, there is evidence of spillover generated from FDI outflow, with Japanese multinationals undertaking direct investments in the United States. Also, it is found that multinationals invest more on R&D and having better management skill than domestic firms in the United Kingdom (Branstetter 2006; Griffith, Redding, and Simpson 2006; and Fu et al. 2012).

depend on absorptive capacity, such as innovation-complementary assets in the host region (Javorcik 2004; Smeets 2008; Fu et al. 2011 and 2012).

Therefore, my hypothesis is that exporters are more likely to benefit from interaction with foreign investors, which are most likely to have higher-level technology. However, this hypothesis is based on the assumption that Tunisian manufacturing firms have the internal absorptive capacity to benefit from FDI.

I construct a dummy variable of FDI with firms' ownership information from the INS data.

FDI_{ijt} = 1, if there is any foreign ownership, and 0, otherwise.

Equation (1.4) below tests the additional interaction of FDI with the interaction term of export and technology gap. As mentioned above, I expect that FDI would have a positive effect on the relation between exports and convergence, since it might further facilitate technology spillover, especially in developing countries where technology is far behind the frontier.

$$\Delta \ln A_{ijt} = \beta_a \text{Export}_{ijt-1} + \beta_b \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_c FDI_{ijt-1} + \beta_d \text{Export}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1}$$

$$+ \beta_e \text{Export}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} \times FDI_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \qquad (1.4)$$

Moreover, innovation is widely used as a proxy for firms' ability to adopt existing technology (absorptive capacity[14]), which influences convergence. While growth theories consider distance from the frontier to be a measure of this absorptive capacity, as the farther a firm is from the frontier, the more technology there is to be transferred; literature on innovation considers absorptive capacity of a firm to be a function of its own internal level of innovation and technology.

Firms need a certain level of innovation and technology before they can benefit from new technologies discovered by other firms, and increased innovation, such as investment in R&D, help boost efficiency indirectly because these activities speed up the assimilation of technologies developed outside the domestic sector (Girma 2005; Fu 2008). In this regard, those firms far from the frontier might not be able to converge to the frontier because a certain level of innovation and technology is required to benefit from new technologies discovered by others. In fact, the role of innovation varies depending on the country's

14. Absorptive capacity is a term that describes firms' ability to identify, assimilate, and exploit knowledge from the environment (Cohen and Levinthal 1990). There are a number of different proxies for measuring the absorptive capacity, such as R&D intensities and human capital embodied in local firms.

relative position in technology advancement, and the relationship between innovation and productivity shows the inverse U shape (Aghion and Howitt 2006).

Innovation often accompanies the decision to export, for instance, in the form of large R&D investment. Also, an expansion of the export market is shown to increase both exporting and R&D and generate a gradual within-plant productivity improvement (Aw et al. 2011). Innovation is correlated with a large proportion of exporters within an industry and also with TFP increase in the industry. A firm self-selects into innovation activities when anticipating its entry into export markets (Van Beveren and Vandenbussche 2010). At the same time, investment on R&D and IT seems to drive process innovations for exporters (Brynjolfsson and Hitt 2003; Bernard et al. 2011).

The INS data provides detailed information about expenses on innovation activities, such as conducting R&D, receiving consulting services, and purchasing royalties. These expenses have been widely used as proxies for innovation in the previous literature (Cohen and Levinthal 1990; Griffith et al. 2004; Lokshin et al. 2008; Bloom and Van Reenen 2011). Following on previous literature, I construct an innovation variable using cost items that is directly related to technical innovation, as below.

Ln Innovation = log (cost of conduction R&D + cost of receiving technical consulting services + cost of purchasing royalties)

Regression (1.5) tests the potential interaction effect between innovation and the interaction term of exporting and technology gap. The innovation variable is the sum of the investment amount in activities that are directly related to innovation, including payment to R&D, external royalties, and receiving consulting services. Innovation variables are deflated with an output deflator. While the interaction between innovation and exports could show a positive influence on productivity, given that Tunisian firms are relatively far away from the technology frontier, the expected direction and magnitude of these interaction effects is not clear.

$$\Delta \ln A_{ijt} = \beta_a \text{Export}_{ijt-1} + \beta_b \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_c \ln \text{innovation}_{ijt-1} + \beta_d \text{Export}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1}$$
$$+ \beta_e \text{Export}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} \times \ln \text{innovation}_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \qquad (1.5)$$

5. Concerns from the econometric specification and solutions

There might be several issues related to the econometric strategy above, namely, potential measurement error in export variables, collinearity between industry-invariant unobservables, and firm-specific characteristics, endogenous export decisions, and the definitions of the frontier. For a robustness check, I use different specifications and econometric techniques to deal with the abovementioned issues, and test whether regression results are consistent across them.

Using different export measures in case any measurement errors exist in export variables

Although most of the existing literature has used the previous-year export status to analyze its effect on productivity, there might be other variables to better demonstrate a firm's participation in export. For instance, export volume could provide additional information on export intensity. Also, if there is no time required to transmit learning from exporting to productivity increase, using current export status is more appropriate.

Export volume: Some researchers have used export intensity, such as export volume, instead of an export dummy, to understand exports' effects on productivity. They have found a significantly positive effect of export intensity on productivity growth (Castellani 2002; Girma and Kneller. 2005), but others have found no larger or statistically significant relationship (Aw et al. 2001, Clerides et al. 1998). The benefit of using that value term would be that it captures the information of export intensity. Since the export amount is a continuous variable, the coefficient of export value shows how much a given increase in previous export amount drives TFP growth.

$$\Delta \ln A_{ijt} = \beta_a \, ln \text{ Export Volume}_{ijt-1} + \beta_b \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_c \ln\text{Export Volume}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + X_{ijt-1} + + \alpha + \alpha_j + \alpha_t + \varepsilon_{ijt} \qquad (1.6)$$

- $\beta_a = (d\Delta \ln A / d \ln \text{Export})(\ln\text{Export} / \ln\Delta A)$ is the elasticity of productivity growth with respect to the export volume

Current year exporting status

As explained in the previous section 4. Empirical Strategy, I initially used the previous export status as I assumed the export would take time, perhaps at least one year, to influence productivity. Therefore, firms' participation in exporting would influence TFP level in the following year, thus affecting productivity growth. But if my assumption on required time for transmitting learning from exporting to productivity does not hold, the export status would influence same-year productivity level and growth. Therefore, I use current-year export status.

$$\Delta \ln A_{ijt} = \beta_a \text{ Export}_{ijt} + \beta_b \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_c \text{Export}_{ijt} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + X_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \qquad (1.7)$$

Using different fixed effects to deal with the potential collinearity between industry-invariant unobservables and firm-specific characteristics

As explained in the previous section, I control for unobserved heterogeneity that is correlated with the explanatory variables by allowing the error term (U_{ijt}) to include a firm-specific fixed effect (α_i), a full set of year dummies (α_t), and industry dummies (α_j) to control for a specific trend of common macroeconomic shocks that affect rate of TFP growth. Because some firms have changed their industry over time, in several industries, industry dummies and firm-fixed effects are not perfectly correlated.

However, in some industries, industry dummies are perfectly correlated with firm-fixed effects. Therefore, I test the baseline specification, without industry-fixed effects, and test whether the results are consistent with and without the alternate specification. In addition, to capture unobservable potential macroeconomic shocks and industry heterogeneity while keeping firm-fixed effects, I use an interaction term of time dummies and industry dummies, to avoid high collinearity of some of the industry- and firm-fixed effects, to examine whether the test results are consistent across specifications.

Endogeneity in exporting decisions

In equation (1.3) if firms with faster productivity growth become exporters, the coefficient of exports might be biased. Export status might be correlated with unobserved firm characteristics, other than the initial productivity level, that would directly influence future productivity level, and thus productivity growth. Therefore, the empirical specification in equation (1.3) might fail to convincingly isolate the causal effect of exporting on firm productivity growth.

To understand the causal effect between exporting and productivity, I first apply generalized method of moments (GMM) in measuring equation (1.3), to deal with potential endogeneity in the export decision. In case the decision to participate in exporting is correlated with productivity level (endogeneity), GMM eliminates this endogeneity issue by using the dependent variable and export status as its own instrument, by removing them from the regression equation (using the differenced equation with lagged levels as instruments) or by removing them from the instruments (using differences as an instrument in a levels regression).

Additionally, as a robustness check, I use external instrumental variables (IVs) for exports to deal with the potential bias caused by endogenous export status. The benefit of using IV over GMM would be that since INS data is weakly balanced panel data, I lose significant numbers of firm observations when using GMM, which requires previous years information. The suggested instrument is "international market demand," which is measured as a sum of import values of France, Italy, and Germany, which are Tunisia's major export destinations (IV1). The import values are those countries' imports from the rest of the world by two-digit industry. Since Tunisia is a small economy, it is unlikely that Tunisian firms would influence the international market demand, while it is likely that the export volume of Tunisian firms would be correlated with the international market demand. Also, the timing and patterns of international market demand for each industry were unforeseen. Therefore, this instrument plausibly satisfies the requirement that the instrument be uncorrelated with the ultimate outcomes of interest except via the channel of interest (the change in export status).

However, the international market demand is industry-level information and does not provide firm-specific information. Therefore, I deduct firms' sales revenue from the international market demand (IV2). So now the intuitive interpretation for IV2 is the potential world market of firm *i* where firm *i* can export, in addition to current sales volume, and this provides a firm-level instrument.[15] By using this IV, I expect the coefficient of 2SLS would be reduced, by elimination of the global market demand change factor.

I run the following regression to see whether suggested IV (IV2) is a strong instrument.

$$\text{Export status}_{ijt-1} = \delta + \beta_a\, IV2_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \tag{1.8}$$

Here, δ is a constant term and ε_{ijt} is a serially uncorrelated error. Because the impact of firm-level international market demand (IV2) on firm-specific export status may vary by years and industry, I include year and industry dummies, α_j and α_t, respectively. Also, this impact may vary by individual firm characteristics, so I also run another regression with firm-fixed effects. Table 1.3 shows that the suggested IV explains significant variations of the instrumented variable, export status.

Table 1.3 The Relation between International Demand (IV) and Export Status

Dep.var. export status	(1) IV2_OLS	(2) IV2_FE
IV2	0.233***	0.092**
	(0.000)	(0.002)
Constant	-5.584***	-2.172**

15. I have also considered constructing firm-specific IV by multiplying the international market demand and firms' sales revenue (IV3). However, this IV does not explain much variation in export status. I therefore do not use this IV. The coefficient of OLS regression for IV3 on export status is significant but less than 0.10.

	(1)	(2)
	(0.000)	(0.003)
Observations	11,987	11,987
R^2	0.365	0.258*

Note: Year and industry dummies were included but not reported. Standard errors are corrected and robust (white correction for heteroskedasticity). *P*-values in parentheses, significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, * Reported R^2 for fixed effect is between groups.

Table 1.3 shows that the suggested IV (IV2) has a positive and statistically significant effect on export status, and is therefore relevant. To test the strength of the instruments, I also test *F*-statics of OLS regression of IV on the endogenous variable, which is essentially the same as column (1) in table 1.3 but without year and industry dummies, α_j and α_t. The *F* test results confirms the strength of instrument (*F* (1, 11,987=16.73 and Prob. > *F* = 0.00).[16]

The predicted export status is in the range below 0 or 1. Given that actual export status is a dummy variable, this model is essentially linear probability model, which allows me to use the predicted value in the second stage model[17]. I also use export volume as an instrumented variable, as a robustness check. Table D.5 in appendix D shows that the IV2 explains significant variations of export volume as well.

Since equation (1.3) includes an endogenous variable (export status) and its interaction term with technology distance, using stata commands such as ivreg2 or xtivreg2 treats them as if they are two endogenous variables and requires more than one instrument, which is unnecessary. Therefore, I conduct two-stage regression manually by estimating the predicted value of the previous export status ($\mathit{Predicted}\ \mathrm{Export\ status}_{\mathrm{ijt-1}}$) which is a function of $IV2_{\mathrm{ijt-1}}$ as seen in equation (1.8).

Also, I generate an interaction term of $\mathit{Predicted}\ \mathrm{Export\ status}_{\mathrm{ijt-1}}$ and previous-year technology distance variable. Then, I plug these predicted variables, which are $\mathit{Predicted}\ \mathrm{Export\ status}_{\mathrm{ijt-1}}$ and $\mathit{Predicted}\ \mathrm{Export\ Statuse}_{\mathrm{ijt-1}} \times \ \ln\left(\frac{\mathrm{TFP_F}}{\mathrm{TFP_i}}\right)_{\mathrm{jt-1}}$ into equation (1.3).

Since the OLS standard errors from the manually conducted second stage will be incorrect, I manually correct the standard errors (Angrist and Pischke 2009).[18]

16. To show the strength of instruments, a common rule of thumb is that the *F*-statistic against the null that the excluded instruments that are irrelevant in the first-stage regression should be larger than 10, for models with one endogenous regressor (Angrist and Pischke 2009).

17. In the case of nonlinear model, such as probit, residual can be correlated with the fitted value and regressors; therefore, plugging in its predicted value in the second stage is so-called forbidden regression (Hausmann 1975).

18. The OLS standard errors from the manual second stage will be larger than the correct one since it includes not only the variance of the second stage, but also the variance generated by the difference between actual value and predicted value (Angrist and Pischke 2009). Therefore, I correct the standard error by using an actual value, instead of predicted

The second-stage regression is now:

$$\Delta \ln A_{ijt} = \beta_a \textit{Predicted} \text{ Export stat}_{ijt-1} + \beta_b \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_c \textit{Predicted} \text{ Export Stat}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1}$$

$$+ X_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \quad (1.9)$$

Different measures of technology frontier and technology distance

There might be a concern if the technology frontier identified above is an outlier for a certain year or if technology is transferred from the international frontier rather than the domestic frontier. Here, I suggest new measures of the technology frontiers for the robustness check that allows me to compare the current frontier with a set of high productivity firms (top 1 percent frontier) and to compare the differences in domestic frontier and international frontier, using available information, which is labor productivity.

Appendix C provides additional information on these new measures of technology frontier and Tunisian firms' technology distance to these new frontiers. The similar level and pattern between the initial frontier/distance and the top 1 percent frontier/distance, as well as the international and the domestic frontier/distance, using labor productivity, ensure that the initially identified technology distance measure is a good measure for the technology transfer from technologically more advanced domestic firms to less advanced firms, and a good, although indirect, proxy for technology transfer from foreign firm to domestic firm.

- *Top 1 percent frontier*

There might be a concern if the identified technology frontier, which is a firm with the highest TFP level in industry *j* and time *t*, is an outlier for a certain year.

Therefore, I generate another frontier measure, by taking the average TFP of firms that have top 1 percent of TFP level in industry *j* and year *t* (Frontier–top 1 percent). Now the technology distance is a log difference of the frontier 2 and TFP level of an individual firm that belongs to bottom 99 percent of TFP in industry *j* and time *t* (Distance–top 1 percent).

Table 1.4 compares these new frontier and distance measures and the previous frontier (Frontier–the highest) and the previous distance (Distance–the highest). As expected, the Frontier–top 1 percent has a smaller value than Frontier–the highest, therefore the

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value, in measuring the residual of second-stage regression and then using that in estimating the standard errors of coefficients. Baum has provided stata code to correct the 2 stage estimation standard errors.

Distance–top 1 percent is also smaller than the Distance–the highest. Graphs C.1 and C.2 in appendix C provide the average and standard deviation of this new measure of technology distance (Distance–top 1 percent); this shows a very similar pattern to the graphs 1.3 and 1.4 in section 3 (Data and Variables), which provide the initial distance variable (Distance–the highest).

Table 1.4 Comparison of Different Technology Frontiers and Distances

Variables	Description	Obs.	Mean	SD	Min.	Max.
Frontier–the highest	Highest TFP in industry *j* and time *t* in Tunisia	16,473	2.37	0.93	-0.34	6.38
Distance–the highest	Distance from frontier 1	15,749	2.36	1.15	0.00	9.33
Frontier–top 1%	Average top 1% TFP in industry *j* and time *t* in Tunisia	16,473	2.10	0.75	-0.34	6.38
Distance–top 1%	Distance from frontier 2	15,434	2.13	0.97	0.00	9.32

- *International versus domestic frontier, using labor productivity*

As mentioned before, domestic distance might be a more relevant measure than international distance for examining firm-level convergence in developing countries, where firms are more likely to learn from other in-country firms rather than from foreign ones (Bartelsman et al. 2008).

Meanwhile, domestic distance might not be a good measure to test export's role in technology transfer since one could argue that participating exporting activities could bring technology transfer from technologically advanced foreign firms (international frontier) to domestic exporters. However, because there is no available TFP information for international frontier firms, I use domestic technology distance to test export's role in technology transfer — which might be a concern.

To understand whether domestic technology distance can be a good measure to test export's role in technology transfer, I first check whether domestic frontiers have more exposure to international markets than other firms. However, I find that domestic technology frontier firms (244 firms from 22 industries for 11 years) do not have greater participation in exporting activities than other firms, although they have greater exposure to foreign investment than other firms, which could also lead to learning from internationally advanced firms. Specifically, among domestic technology frontier firms, about 50 percent are exporters and some 40 percent received FDI. Meanwhile, among the rest of the firms, about 50 percent have participated in exporting, but only 27 percent receive FDI (the details are in tables C.5 to C.8 in appendix C). Therefore, domestic technology distance is only an indirect proxy for the technology transfer channel from abroad.

As a robustness check, I measure productivity in a different way, which allows me to obtain international technology distance — the hypothesized source of knowledge spillover in previous literature.

I measure the international distance as the productivity difference between Tunisia and France. I consider France as a benchmark country for Tunisia since France is the largest export destination, and both countries have had close cultural and economic ties.[19] While I cannot obtain firm-level TFP information for France, average labor productivity is available at two-digit industry-level in France, provided by EU KLEMS.[20] Therefore, I consider industry-level labor productivity of France as the international benchmark for Tunisian firms (internal technology frontier).

For the comparison, I measure an additional domestic technology gap using labor productivity of Tunisian firms. This additional frontier is measured by log labor productivity of the firm with the highest labor productivity in industry *i,* time *t.* Now the distance is the distance between this additional technology frontier and the individual firm's log labor productivity in industry *i* and time *t.*

- International frontier, using labor productivity ($L_{FF\,jt}$): French industry-level labor productivity in sector *j,* at time *t*
- Domestic frontier, using labor productivity ($L_{DF\,jt}$): a Tunisian firm that has the highest labor productivity in sector *j,* at time *t*

Table 1.5 compares the international and the domestic technology frontier/ distance, using labor productivity. The technology distance between the domestic and international frontier is not large. Meanwhile, international technology distance has some negative value because some Tunisian firms have a higher labor productivity level than the French industry average labor productivity level. I delete the negative values when I run the following regressions.

19. Tunisia was a French protectorate from 1881 until its independence in 1956. Its legal system and institutions were heavily influenced by France. French is an official language. France is Tunisia's largest foreign investor and trade partner.
20. 2011 EU KLEMS data in ISIC Rev.3 provides a limited set of variables for 72 industries up to 2007. I use the output data at current basic prices (in millions of euros), deflated by the price indexes, provided by the EU KLEMS. I convert year 2000 as a base year of price indexes to be consistent with Tunisian data. Then, I convert it to Tunisian dinars, using exchange rates provided by IMF. Then I divide this deflated output by number of persons employed, which is also provided in EU KLEMS.

Table 1.5 International and Domestic Frontiers/ Distance, Using Labor Productivity

Variables	Description	Obs.	Mean	SD	Min.	Max.
Domestic LP frontier, $L_{DF\,jt}$	Labor productivity of the Tunisian firm that has the highest labor productivity in sector *j*, at time *t*	16,473	13.3	1.3	9.3	16.1
Domestic LP distance	Distance from the domestic frontier	16,464	3.4	1.8	0.0	12.5
International LP frontier $L_{FF\,jt}$	French industry-level labor productivity in sector *j*, at time *t*	16,473	11.8	0.5	10.9	13.0
International LP distance	Distance from the international frontier	16,464	1.8	1.1	-4.4	8.2

I test the main equation (1.3), using this international distance and domestic distance, using labor productivity as seen in equations (1.10) and (1.11).

$$\Delta \ln A_{ijt} = \beta_a \text{ Export}_{ijt-1} + \beta_b \ln\left(\frac{LP_{FF}}{LP_i}\right)_{jt-1} + \beta_c \text{Export}_{ijt-1} \times \ln\left(\frac{LP_{FF}}{LP_i}\right)_{jt-1} + X_{ijt-1} + \alpha_i + \alpha_t + \varepsilon_{ijt} \quad (1.10)$$

$$\Delta \ln A_{ijt} = \beta_a \text{ Export}_{ijt-1} + \beta_b \ln\left(\frac{LP_{DF}}{LP_i}\right)_{jt-1} + \beta_c \text{Export}_{ijt-1} \times \ln\left(\frac{LP_{DF}}{LP_i}\right)_{jt-1} + X_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt}$$

(1.11)

Compared to TFP, labor productivity is a less preferable measure since it cannot capture other input factors such as capital, which affects the process of technology transfer. However, a benefit of using labor productivity–based technology distance in the above specification is that it can avoid a potential collinearity problem in the regression — using the TFP-based measure in the equation (1.3) results in that the TFP variable is in both the right hand side (RHS) and the left hand side (LHS) of the equation.

6. Results

Evidence of unconditional convergence

Table 1.6 provides evidence of unconditional convergence among Tunisian manufacturing firms. Specifically, column (1) provides the results of equation (1.1), which tests the relationship between technology distance and productivity growth, without firm-fixed effects as well as any other control variables (unconditional convergence).

The coefficient of technology transfer is 0.067, which means that 1.0 percent increase in the technology gap corresponds to 6.7 percent increase in productivity growth rate. For instance, if productivity growth were 2.000 percent per annum, this would increase to 2.134 percent per annum (2.000 × 1.067 = 2.134). This also means that it takes less than eight years to eliminate 50 percent of the initial gap, regardless of firm-specific characteristics, such as manager's capability and workers' skills, which are often unobservable factors that could influence a firm's productivity growth. This finding is remarkable and in contrast to previous findings that do not find unconditional convergence at the country- and industry- levels.

I also add columns (2) to (6) to show how the convergence pattern is changed based on the conditions included in each column. In columns (2) and (3), I have added the export variable and the interaction between export and technology distance, which are key variables of this paper. Columns (2) and (3), therefore, show a convergence pattern controlling firms participating in export. The coefficients remain the same in column (2) when including export, and slightly decrease in column (4).

Columns (4) to (6) are duplications of columns (1) to (3) without firm-fixed effects, but include time and industry dummies. Coefficients of tech distance are increased more than those in columns (1) to (3), implying that convergence patterns are stronger when controlling industry-specific characteristics and time shocks. This pattern of larger coefficients when there is additional control of industry/ time dummies is consistent with the previous cross-countries study, which finds that the estimated convergence coefficients decreased when country dummies were excluded (Rodrik 2012).

Table 1.6 Evidence of Unconditional Convergence

Dep. var. = TFP growth	OLS Without time and industry dummies			OLS With time and industry dummies		
	(1)	(2)	(3)	(4)	(5)	(6)
Exporter		-0.007	-0.046*		-0.007	-0.062**
		(0.242)	(0.034)		(0.369)	(0.006)
Lag Ln tech distance	0.067***	0.067***	0.058***	0.095***	0.095***	0.085***
(lag ln TFP_Fj/ln TFP_ij)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exporter* Ln tech distance			0.017			0.025**
			(0.054)			(0.008)
Constant	-0.161***	-0.157***	-0.138***	-0.288***	-0.290***	-0.260***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11,428	11,428	11,428	11,428	11,428	11,428
R^2	0.031	0.031	0.032	0.047	0.047	0.048

Note: Standard errors are clustered, and robust (white correction for heteroskedasticity).
P-values in parentheses, significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 1.7 provides the results for equation 1.3, which is using firm-fixed effects. The dependent variable is TFP growth for all the firms in manufacturing. The regressors are previous export status, the log of initial productivity level relative to technology frontier, interaction term of the previous export status, and relative productivity. Each regression is run with two-digit–level industry and year dummies, as well as firm-fixed effects. Random effect and Hausman test results are provided in table D.6 and D.7 in appendix D and show that fixed effect is a better estimate than random effect.

Table 1.7 Results with Firm-Fixed Effect, with Export Dummy

Dep. var. = TFP growth	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
Lag exporter	-0.023		-0.043**	-0.203***	-0.202***
	(0.104)		(0.002)	(0.000)	(0.000)
Tech distance		0.145***	0.145***	0.120***	0.120***
(Lag ln TFP_Fj/TFP_ij)		(0.000)	(0.000)	(0.000)	(0.000)
Lag exporter*tech distance				0.071***	0.071***
				(0.000)	(0.000)
Lag innovation investment					-0.001
					(0.249)
Lag FDI status					-0.014
					(0.572)
Constant	0.150	-0.335	-0.336	-0.253	-0.235
	(0.586)	(0.254)	(0.260)	(0.412)	(0.446)
Observations	11,428	11,428	11,428	11,428	11,428
R^2	0.013	0.081	0.082	0.088	0.088

Note: With firm-fixed effects. Year dummy and industry dummy were included but not reported. Standard errors are clustered at the firm level, and robust (white correction for heteroskedasticity).
P-values in parentheses, significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Now the coefficients of technology distance in table 1.7 become larger than those in table 1.6. Including firm-fixed effects would result in an upward bias in the coefficient, if firm-specific conditions that are correlated with initial productivity, such as manager's characteristics, workers' skills, and firm's location, play a role in determining the speed of convergence. These results are in line with Rodrik (2012), who shows that coefficients of technology transfer increased when country-fixed effects were included, and Barro (2012), who explains that growth regressions with country-fixed effects could yield upwardly biased estimates of the convergence rate when the time horizon is short, due to the Nickell bias.[21] Therefore, the estimated coefficient in table 1.7 can be the upper bound of gauging the magnitude of the convergence rates.

Column (1) shows the role played by exports in determining rates of TFP growth, excluding other terms. The coefficient is statistically insignificant, but becomes negative in other columns when I add technology transfer and other terms. The magnitude of the coefficient becomes larger when an interaction term between export and technology gap is added. This might be explained by the fact that more productive firms are more likely to be exporters (by self-selection), thereby increasing their productivity more slowly than those firms that are further behind the technology frontier.

In fact, exporters have a higher productivity level than non-exporters, which could support the possibility of self-selection in exporting activities. Table 1.7a shows that, on average, exporters have a higher TFP level than non-exporters.

Table 1.7b provides regression results of export status (dummy) and export value (intensity) on TFP level, with and without time and industry dummies. Columns (1) to (4) are estimation results using OLS, which show that both export status and export value have significant and positive coefficients on TFP level. Columns (5) to (8) show the estimation results using firm-fixed effect. The coefficients of export dummy variables become statistically insignificant; however, the coefficients of export value are still statistically significant and positive, although the magnitude becomes smaller than those with OLS estimation.

Table 1.7c provides the estimation results that duplicated the estimation of table 1.7b, but by using labor productivity as a dependent variable instead of using TFP. The magnitude of coefficients for both export dummy and export value become much larger than those with TFP as dependent variable, in columns (1) to (4). With firm-fixed effect, the coefficients become smaller but are still positive and statistically significant, as seen in columns (5) to (8).

These results are quite similar to other studies on different countries. For instance, Bernard and Jensen (1995) found that exporters show higher productivity level in US manufacturing (3 percent for TFP and 11 percent for value added per worker). Here I use labor productivity, instead of value added per worker, which has a higher value on the dependent variable and could explain the larger export premium in table 1.7c.

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21. Nickell (1981) shows that the estimate of the coefficient on the lagged dependent variable is biased downwards in the presence of a fixed effect. If there is persistence in the level of the dependent variable, which is underestimated, the estimated convergence rate tends to be overestimated. This so-called Nickell bias tends to zero as the time span gets large, but can be large in short panels.

Table 1.7a Average TFP Level between Exporters and Non-exporters

	Exporters	Non-exporters
Mean	0.0366	-.0206
(SD)	(0.702)	(0.665)
Observations	8,080	7,669

Table 1.7b Regression Result of Export Dummy (Value) on TFP Level

	OLS				FE			
	(1) Without industry and time dummy	(2) With industry and time dummy	(3) Without industry and time dummy	(4) With industry and time dummy	(5) Without industry and time dummy	(6) With industry and time dummy	(7) Without industry and time dummy	(8) With industry and time dummy
Export dummy	0.054*	0.057*			0.009	0.014		
	(0.013)	(0.021)			(0.366)	(0.226)		
Export value			0.006***	0.007***			0.002***	0.003***
			(0.000)	(0.000)			(0.001)	(0.000)
Constant	-0.019	-0.007	-0.042**	0.010	0.004	- 0.346***	-0.009	-0.346
	(0.203)	(0.663)	(0.006)	(0.608)	(0.473)	(0.200)	(0.107)	(0.204)
# of obs.	15,749	15,749	15,749	15,749	15,749	15,749	15,749	15,749
R^2	0.017	0.017	0.020	0.029	0.000	0.015	0.001	0.017
Rho	n.a.	n.a.	n.a.	n.a.	0.8034	0.830	0.804	0.829

Note: Standard errors are clustered, and robust (white correction for heteroskedasticity), n.a. = not applicable. P-values in parentheses, significance level: * p < 0.05, ** p < 0.01, *** p < 0.001, overall R2 are reported fixed-effects estimation, rho reports fraction of variance due to u_i. for fixed-effect estimates.

Table 1.7c Regression Result of Export Dummy (Value) on Labor Productivity Level

	OLS				FE			
	(1) Without industry and time dummy	(2) With industry and time dummy	(3) Without industry and time dummy	(4) With industry and time dummy	(5) Without industry and time dummy	(6) With industry and time dummy	(7) Without industry and time dummy	(8) With industry and time dummy
Export dummy	0.308***	0.276***			0.070***	0.055**		
	(0.000)	(0.000)			(0.000)	(0.001)		
Export value			0.029***	0.028***			0.008***	0.009***
			(0.000)	(0.000)			(0.000)	(0.000)
Constant	9.775***	9.746***	9.710***	9.741***	9.897***	9.862***	9.867***	9.863***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# of obs.	16,464	16,464	16,464	16,464	16,464	16,464	16,464	16,464
R^2	0.332	0.336	0.345	0.349	0.002	0.012	0.007	0.017

Rho	n.a.	n.a.	n.a.	n.a.	0.862	0.868	0.862	0.869

Note: Standard errors are clustered, and robust (white correction for heteroskedasticity), n.a. = not applicable. *P*-values in parentheses, significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, overall R^2 are reported for fixed-effects estimation, rho reports fraction of variance due to u_i for fixed effect estimates.

In table 1.7, the coefficient of technology gap variable is positive and statistically significant, across different specifications from columns (1) to (5), indicating that the further away firms are from the technology frontier, the faster they grow.

The estimated technology transfer coefficients are the elasticity of technology gap changes related to productivity growth rate and are in the range of 12.0 to 14.5 percent. This means that 1.0 percent increase in the technology gap corresponds to 12.0 to 14.5 percent increase in productivity growth. Therefore, if the productivity growth were, for instance, 2.00 percent per annum, 1.00 percent further away from the technology distance would increase to 2.24 to 2.29 percent per annum (2.00 × 1.145 percent = 2.29 percent).

This coefficient is almost twice larger than Griffith et al.'s (2004), who provided industry-level convergence evidence across OECD countries. Their coefficient of log technology transfer term on log TFP growth, which is directly comparable with my coefficient of technology transfer, is in the range between 6.7 and 8.0 percent. This coefficient is much larger than Rodrik's (2012), who provided industry-level convergence across a wider group of countries, including a number of developing countries. His coefficient of log initial labor productivity on log labor productivity growth is in the range between 5.4 to 6.0 percent, which is not directly comparable with my estimated coefficient of technology transfer, but still provides valuable information as a cross-check.

The faster convergence pattern in my results, compared to others, might be explained by the fact that firms in developing countries like Tunisia are at a lower level of productivity to start with; therefore, they have faster productivity growth than firms in OECD countries, as in Griffith et al. (2005).

Another explanation for the faster convergence pattern in my results, compared to others, could be that a lack of firm entry and exit dynamics prevents firm-level convergence adding up to aggregated convergence of industry. Industry productivity growth consists of existing firm productivity growth and the set of firm changes (productive firms enter and less productive firms exit), which reallocate resources across firms and industries, and so enhance aggregated productivity. If firm entry and exit dynamics are below the optimal level, caused by the complex regulatory environment for establishing firms, difficulties in access to finance or lack of entrepreneurship (for firm entry), and complex regulations for closing businesses or bankruptcy (for firm exit), firm-level convergence does not add up to aggregated convergence at industry level.

This is similar to Rodrik's explanation for why industry-level convergence does not add up to aggregated convergence of a whole economy, due to the lack of structural transformation, which implies production resources from less productive industry move to more productive industry. His coefficient also gets larger when the level of disaggregation gets larger (from two to four digits), which might strengthen my explanation for higher micro-level convergence, but lower aggregated convergence of manufacturing.

In fact, El Arbi Chaffai et al. (2009) compare Tunisian industry-level TFP and OECD member countries' TFP for six manufacturing industries for the earlier period than my data analysis. Their results show that the TFP distance between Tunisian TFP and OECD countries has been slightly reduced only in some industries, which also suggests that the convergence rate might not be very high at industry level in Tunisia.[22] In addition, Marouani and Mouelhi (2013) argue that productivity increase within industry did not lead to structural change across industries, due to entry barriers in some sectors, the inefficiently of factor markets, and firms upgrading programs only in a few select industries. As a result, overall labor productivity has remained relatively low. These previous findings might also indirectly support the conclusion that firm-level convergence often does not add up to industry-level convergence.

The purpose of the interaction term between export and technology transfer is to test export's role in technology transfer. As expected, the coefficients of this interaction term are positive and statistically significant at 0.1 percent level in columns (4) and (5) in table 1.7. This implies that the further a non-frontier firm lies behind the frontier (the larger gap variable), the greater the potential for technologies to be transferred through exporting, and the higher the rates of productivity growth. In addition, while the linear export term is negative, as explained above, the linear term of the gap variable remains positive and significant. This might support my explanation on the negative coefficient of exports. While exporters in general do not show faster productivity growth, since they are closer to the technology frontier, those far behind the technology frontier grow even faster when they export.

22. El Arbi Chaffai et al. (2009) provide Tunisian industry-level convergence pattern of OECD member countries in six manufacturing sectors from 1983 to 2002; therefore, I cannot directly compare the technology transfer coefficient rates with theirs. In fact, they have not used an empirical model similar to mine, nor provide the convergence rates. But they have provided the TFP trends over time for six manufacturing industries, together with other countries' industry-level TFP levels, which demonstrates the trend of the industry-level distance to international technology. As mentioned before, the technology gap with other OECD countries has been slightly reduced in the textiles and leather, building and ceramics, and chemical industries, while the gap has been increased in electronics and metal, and food processing.

Column (5) reports the results with control variables, lagged innovation input investment amount, and lagged FDI status. The result for the exports, gap, and interaction terms remains the same.

In sum, the regression results show that there are strong convergence patterns among Tunisian firms. Those firms that have lower TFP levels grow faster. Exporting's effect on productivity growth is negative: the further a non-frontier firm lies behind the frontier (the larger gap variable), the greater the potential for technologies to be transferred through exporting; thus, the higher the rates of productivity growth. This finding also suggests that without considering the convergence effect and its interaction effect with exports, looking only into exports' effect on productivity would underestimate the learning by exporting effect.

Moderating effects of FDI and innovation

Table 1.8 provides the baseline specification, regression (3) with the additional interaction terms of FDI and innovation, which might be additional factors that influence export's effect on productivity.

Table 1.8 Three-Way Interaction (Tech Distance × Export × FDI vs. Tech Distance × Export × Innovation)

Dep. var. = TFP growth	(1) FE	(2) FE-interaction with FDI	(3) FE-interaction with innov.	(4) FE-both
Lag exporter	-0.202***	-0.201***	-0.211***	-0.210***
	(0.000)	(0.000)	(0.000)	(0.000)
Tech distance (Lag Ln TFP_Fj/TFP_ij)	0.120***	0.119***	0.120***	0.118***
	(0.000)	(0.000)	(0.000)	(0.000)
Lag exporter × tech distance	0.071***	0.062***	0.091***	0.084***
	(0.000)	(0.000)	(0.000)	(0.000)
Lag innovation	-0.001	-0.001	0.002	0.003
	(0.249)	(0.286)	(0.296)	(0.157)
Lag FDI status	-0.014	-0.089*	-0.010	-0.094*
	(0.572)	(0.025)	(0.693)	(0.018)
Lgap exp fdi		0.040**		0.045**
		(0.007)		(0.003)
Lgap exp inno			-0.003**	-0.003**

	(1)	(2)	(3)	(4)
			(0.006)	(0.002)
Constant	-0.235	-0.178	-0.259	-0.200
	(0.446)	(0.570)	(0.399)	(0.523)
Observations	11,428	11,428	11,428	11,428
R^2	0.088	0.090	0.089	0.092
F_f	0.991	0.997	0.991	0.999
Rho	0.582	0.598	0.579	0.596

Note: With firm-fixed effects. Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity).
P-values in parentheses, significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, F_f reports F test that all u_i=0 and rho reports that fraction of variance due to u_i.

Column (1) in table 1.8 is the baseline specification for the comparison.

Column (2) includes the three-way interactions among previous-year FDI status, previous-year export status, and previous-year technology gap. As expected, FDI has a positive and significant effect on the relation between export and convergence, which implies that it further facilitates technology spill over, especially for exporters that are far behind the frontier. Specifically, in column (2), the estimated technology transfer coefficients are 11.9 percent, implying that 1.0 percent increase in the technology gap corresponds to 11.9 percent increase in productivity growth (If mean productivity growth was, say 2.00 percent per annum, this would increase to 2.29 percent per annum, since 2.000 × 1.119 percent = 2.240 percent). But this convergence rate will be 6.2 percent higher for exporters, and it will be an additional 4.0 percent higher if the firms also have foreign ownership (FDI). Therefore, those firms that are exporting and at the same time have foreign ownership will have a convergence rate of 22.1 percent (22.1 = 11.9 + 6.2 + 4.0), which is almost twice faster than non-exporters and non-FDI firms.

Column (3) shows the results with a three-way interaction term, with innovation. The coefficient of innovation is negative and significant, although the magnitude of the coefficient is very small. This might be explained by that the innovation effect varies depending on the distance from the technology frontier, and the relationship between innovation and productivity shows an inverted U-shape (Aghion and Howitt 2006). The negative coefficient of innovation might be caused by the fact that Tunisian firms are behind the technology frontier, and therefore form the left-side tail of the inverted U-shape.

Robustness checks

*Different export variab*les*:* The results in table 1.7 are consistent when I use different export measures, as shown in tables 1.9 and 1.10.

Table 1.9 Regression Results with Firm-Fixed Effects, with Export Value

Dep. var. = TFP growth	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Lag export value	-0.002*		-0.004***	-0.014***	-0.014***
	(0.011)		(0.000)	(0.000)	(0.000)
Tech d distance		0.145***	0.145***	0.121***	0.121***
(Lag ln TFP_Fj/TFP_ij)		(0.000)	(0.000)	(0.000)	(0.000)
Lag exporter value × tech distance				0.005***	0.005***
				(0.000)	(0.000)
Lag innovation					-0.001
					(0.275)
Lag FDI status					-0.012
					(0.611)
Constant	0.139	-0.339	-0.347	-0.277	-0.260
	(0.616)	(0.249)	(0.247)	(0.367)	(0.397)
Observations	11,422	11,422	11,422	11,422	11,422
R^2	0.013	0.081	0.083	0.089	0.089
F_f	0.853	0.969	0.974	0.996	0.993
Rho	0.563	0.567	0.574	0.584	0.584

Note: With firm-fixed effects. Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity).
P-values in parentheses, significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, F_f reports F test that all u_i=0 and rho reports that fraction of variance due to u_i.

Table 1.9 shows the results when I use previous-year export value, deflated by the output deflator, instead of using a previous-year export dummy. The results are consistent with table 1.7 which I use export dummy. The coefficient of export value shows the association between percentage increase in the previous export amount and TFP growth generated. While the absolute magnitude of the coefficient of export and interaction terms become slightly smaller than in the previous table 1.7, the direction and statistical significance of coefficients remain the same between both tables.

Table 1.10 Regression Results Firm-Fixed Effects, with Current-Year Export Dummy

Dep. var. = TFP growth	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Exporter	0.002		-0.003	-0.128***	-0.127***
	(0.891)		(0.847)	(0.000)	(0.001)
Tech distance (lag ln TFP_Fj/TFP_ij)		0.145***	0.145***	0.121***	0.122***
		(0.000)	(0.000)	(0.000)	(0.000)
Exporter × tech distance				0.054***	0.054***
				(0.000)	(0.000)

Lag innovation investment					-0.002 (0.189)
Lag FDI status					-0.014 (0.569)
Constant	0.142 (0.604)	-0.339 (0.249)	-0.338 (0.250)	-0.287 (0.340)	-0.267 (0.374)
Observations	11,422	11,422	11,422	11,422	11,422
R2	0.012	0.081	0.081	0.085	0.085
F_f	0.851	0.969	0.969	0.979	0.977
Rho	0.559	0.567	0.567	0.573	0.573

Note: With firm-fixed effects. Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity).
P-values in parentheses, significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, F_f reports F test that all u_i=0 and rho reports that fraction of variance due to u_i

Table 1.10 shows the results when I use current-year export status rather than previous-year export status. The results are consistent with table 1.7 which I use previous-year export status because I assumed that exporting would take time, and therefore, export status would influence TFP during the following year. But if export immediately affects productivity, the current-year export status can assess current-year productivity level and growth. Therefore, I used current-year export status and obtained results consistent with results for previous-year export status.

Different fixed effects: The results in table 1.7 are consistent when I use different fixed effects, as shown in tables 1.11, to deal with potential collinearity between industry-invariant unobservable and firm-specific characteristics.

Table 1.11 Fixed Effects, with Export Dummy, Plus Different Time and Industry Dummies

Dep. var. = TFP growth	(1) FE-time dummy	(2) FE-time dummy	(3) FE-time & industry	(4) FE-time & industry	(5) FE-time × industry	(6) FE-time × industry
Lag exporter	-0.204*** (0.000)	-0.202*** (0.000)	-0.203*** (0.000)	-0.202*** (0.000)	-0.101** (0.003)	-0.100** (0.003)
Tech distance Lag ln (TFP_Fj/ TFP_ij)	0.120*** (0.000)	0.120*** (0.000)	0.120*** (0.000)	0.120*** (0.000)	0.417*** (0.000)	0.417*** (0.000)
Lag exporter × tech distance	0.071*** (0.000)	0.072*** (0.000)	0.071*** (0.000)	0.071*** (0.000)	0.037** (0.006)	0.037** (0.006)
Lag innovation investment		-0.002 (0.208)		-0.001 (0.249)		-0.001 (0.243)
Lag FDI status		-0.015		-0.014		0.004

	(1)	(2)	(3)	(4)	(5)	(6)
		(0.531)		(0.572)		(0.864)
Constant	-0.275***	-0.262***	-0.253	-0.235	-1.845***	-1.842***
	(0.000)	(0.000)	(0.412)	(0.446)	(0.000)	(0.000)
Year dummies	Yes	Yes	Yes	Yes	No	No
Industry dummies (2 digit)	No	No	Yes	Yes	No	No
Time * industry dummies	No	No	No	No	Yes	Yes
Observations	11,428	11,428	11,428	11,428	11,428	11,428
R^2	0.080	0.080	0.088	0.088	0.249	0.250
F_f	1.004	1.004	0.994	0.991	1.572	1.566
Rho	1.004	1.004	0.994	0.991	1.572	1.566

Note: With firm-fixed effects. Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity).
P-values in parentheses, significance level: * p < 0.05, ** p < 0.01, *** p < 0.001, F_f reports F test that all u_i=0 and rho reports that fraction of variance due to u_i.

In columns (1) and (2), I test the baseline specification, without industry dummies, and find that test results are consistent. In columns (3) and (4), I provide the baseline specification, wherein both time and industry dummies are used, as well as firm-fixed effects (this is the same result as in table 1.6). In columns (5) and (6), to capture unobservable potential macroeconomic shocks and industry heterogeneity, while keeping firm-fixed effects, I use interaction terms of time dummies and industry dummies to prevent collinearity of some of the industry- and firm-fixed effects.

As expected, when I have more fixed effects, the magnitude of the coefficient of the technology gap variable becomes much larger, at 41.7 percent, and statistically significant. Meanwhile, the magnitudes of the coefficients of the exporter and interaction terms diminish. Overall, the test results are consistent when different fixed effects are used.

Different Econometric techniques (GMM and IV): The results in table 1.7 are consistent when I use different econometric techniques, GMM and IV, to deal with potential endogenous export decision, as seen in tables 1.12 and 1.13.

Since my specification includes the previous productivity level relative to the technology frontier, unobservables related to the firm's previous productivity level are largely removed. However, if export status is correlated with unobserved firm characteristics, other than the initial productivity level, that would directly influence future productivity level, and thus productivity growth. Therefore, the empirical specification using OLS and FE might fail to convincingly isolate the causal effect of exporting on firm productivity.

Table 1.12 Different Econometric Techniques — GMM

Dep. var. = TFP growth	(1)	(2)
	GMM	GMM
Lag exporter	-0.266*	-0.276*

	(0.047)	(0.045)
Tech distance (Lag ln TFP_Fj/TFP_ij)	0.081*** (0.000)	0.080*** (0.000)
Lag exporter × tech transfer	0.094* (0.033)	0.096* (0.031)
Lag innovation investment		-0.001 (0.207)
Lag FDI status		0.029 (0.116)
Constant	-0.259*** (0.000)	-0.268*** (0.000)
Observations	11,428	11,428
R^2	n.a.	n.a.
AR2 (*p*-value)	0.034	0.036
Sargan, overid. *P*-value	0.000	0.000
Diff-in-Hansen *P*-value	0.965	0.965

Note: Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity), n.a = not applicable.
P-values in parentheses, significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 1.12 provides the estimation results using GMM in measuring equation (1.3). To remove the simultaneity of export decision, I use dependent variable and export status as their own instruments, by removing them from the regression equation (using the differenced equation with lagged levels as an instrument) or by removing them from the instruments (using differences as an instrument in a levels regression).

Specifically, the above results are from non-dynamic system GMM with lag 2 and 3. The instrument set for the differenced equation consists of the log of TFP growth, lagged export status, in levels, in periods $t-2$ and $t-3$ (among which missing values are treated as 0 and the instruments for each period are collapsed), the gap variable, interaction between the gap and previous-year exports, and year and industry dummies, differenced. The instrument set for the levels equation consists of the log of TFP growth, lagged export status, the gap variable, interaction between the gap and previous-year export, a constant, and year and industry dummies.

Overall, the regression results are consistent with previous results in table 1.7. The coefficient of lagged exports is negative and significant at the 5 percent level. The convergence coefficient becomes lower, from 8.0 to 8.1 percent, but is statistically significant. The coefficients of the interaction terms between export and convergence variables become marginally larger.

However, the test results require a careful interpretation of the GMM result. Test results for the AR2 are somewhat small, rejecting the null hypothesis that the differenced residuals in period *t* and *t*-2 are uncorrelated; therefore, autocorrelation in levels might be a concern in this system GMM measurement. The Sargan/Hansen test of over identifying restrictions for the GMM estimators also rejects the null that instruments are exogenous, which might have been caused by the fact that the instrument is exactly identified. A Difference-in-Hansen test fails to reject similar results that these additional instruments are valid.

Additionally, I use external instrumental variables (IV) to deal with the simultaneity issue in the export variable. Tables 1.13 provides the estimation results using instrument variable.

Table 1.13 Different Econometric Techniques — IV 2SLS with Export Dummy

Dep. var. = TFP growth	(1)	(2)	(3)	(4)
	IV2 OLS	IV2 OLS	IV2 Panel	IV2 Panel
Lag exporter	0.076	0.065	-0.344	-0.272
	(0.196)	(0.208)	(0.535)	(0.666)
Tech distance	0.051***	0.051***	0.049***	0.049***
(Lag ln TFP_Fj/TFP_ij)	(0.000)	(0.000)	(0.001)	(0.001)
Lag exporter × tech distance	0.106***	0.109***	0.299**	0.300**
	(0.001)	(0.002)	(0.009)	(0.010)
Lag innovation investment		-0.001		-0.002
		(0.222)		(0.053)
Lag FDI status		0.032**		-0.017
		(0.001)		(0.470)
Constant	-0.323***	-0.318***	-0.348	-0.342
	(0.000)	(0.000)	(0.248)	(0.255)
Observations	11,422	11,422	11,422	11,422
R^2	0.053	0.054	0.116	0.116
Rho	n.a.	n.a.	0.598	0.600
Test regression – Coeff. of IV on the residual of second stage	-0.008***	-0.008***	0.150***	0.149***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2 of the test regression	0.003	0.003	0.064	0.064

Note: Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity) and corrected, n.a. = not applicable.
P-values in parentheses, significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, R2 is reported but it is not important in 2SLS. * Rho is fraction of variance due to u_i. ** R2 of the test regression is from the OLS of IV on the residual of second-stage regression.

Table 1.13 provides the second-stage regression results using predicted value of export status. Columns (1) and (2) provide the estimation results using OLS, and columns (3) and

(4) provide the results using firm-fixed effect. As mentioned before, the instrument used is "the potential world market of firm *i* where firm *i* can export to, in addition to its current sales volume (global market demand).

Instrumenting initial export status reduces the estimated coefficient of technology transfer between 4.9 percent and 5.1 percent in columns (1) to (4). The interaction term between previous export status and technology gap increased significantly for all the specifications using instrument variables, and even more so when I used firm-fixed effects, as shown in columns (3) and (4). Meanwhile, the estimated coefficient of export status becomes insignificant, by eliminating the global market demand change factor. The coefficients of FDI remain positive and significant while the coefficients of innovation remain insignificant.

As mentioned above, I conduct a two-stage (2SLS) model manually with the predicted value of export status and its interaction term with the technology distance. In the empirical strategy section, I provide the first-stage regression result and show that the instrument is relevant since it is strongly correlated with export variables — both export status and volume.

In addition, I conduct additional tests to show whether the suggested instrument is valid; in other words, the instrument affects productivity growth only through export, by showing whether IV2 is correlated with the residual of the second-stage regression. I obtain the residual of the primary regression, which is equation (1.3) and test whether IV has any correlation with this residual. The coefficient of IV on the residual, using OLS with and without innovation and FDI variables, is provided for each column. The coefficient and R^2 of test regression are relatively small and almost close to zero, in case of columns (1) and (2), which ensures that the suggested instrument is not correlated with the residual of the primary instrument (instrument is valid).

As mentioned in the empirical strategy section, I correct standard error by using actual value, instead of predicted value, in measuring the residual of second-stage regression and in estimating the standard error of coefficients. The corrected standard error is much smaller in OLS regression, in columns (1) and (2), which is expected.

However, the results using firm-fixed effects, in columns (3) and (4), require careful interpretation. Unlike OLS, standard errors become even larger when they are corrected. Also, the coefficient of instrument and R^2 of test regression get larger in test regressions, which might suggest that the suggested instrument could influence the dependent variable, not only through the endogenous variable, but also through other channels, when firm-specific characteristics are controlled.

Table D.8 in appendix D provides the second-stage regression results with predicted value of export volume using different instruments. The results are similar to those in table 1.13.

Different measurement of technology distance: The results in table 1.7 are consistent when I use different measurement for technology distance, as shown in table 1.14. Specifically, I compare convergence patterns between the highest versus the top 1 percent distance, using TFP; and between the domestic versus the international distance, using labor productivity.

Table 1.14 Comparisons of Different Distance — FE, Lag Export Dummy

Dep. var. = TFP growth	(1) Domestic TFP- the highest	(2) Domestic TFP- the highest	(3) Domestic TFP – Top 1%	(4) Domestic TFP – Top 1%	(5) Domestic LP	(6) Domestic LP	(7) Intl LP	(8) Intl LP
Lag exporter	-0.203***	-0.202***	-0.137***	-0.137***	-0.005	-0.006	0.028	0.028
	(0.000)	(0.000)	(0.001)	(0.001)	(0.868)	(0.822)	(0.243)	(0.250)
Tech distance (Lag ln TFP_Fj/TFP_ij)	0.120***	0.120***	0.150***	0.150***				
	(0.000)	(0.000)	(0.000)	(0.000)				
Dom distance (TUN LP_Fj/LP_ij)					0.108***	0.108***		
					(0.000)	(0.000)		
Int. distance (FRA LP_Fj/LP_ij)							0.364***	0.364***
							(0.000)	(0.000)
Lag exporter × tech transfer	0.071***	0.071***	0.046*	0.046*				
	(0.000)	(0.000)	(0.013)	(0.013)				
Lag exporter × TUN LP GAP					-0.007	-0.007		
					(0.290)	(0.312)		
Lag exporter× FRA LP GAP							-0.024*	-0.024*
							(0.035)	(0.035)
Lag innovation		-0.001		-0.001		0.001		0.000
		(0.253)		(0.270)		(0.315)		(0.683)
Lag FDI status		-0.014		-0.002		-0.018		-0.005
		(0.494)		(0.935)		(0.369)		(0.794)
Constant	-0.253	-0.235	-0.236	-0.223	-0.177	-0.179	-0.310	-0.312
	(0.398)	(0.433)	(0.685)	(0.702)	(0.565)	(0.559)	(0.288)	(0.286)
Observations	11,428	11,428	9,564	9,564	11,428	11,428	11,428	11,428
R^{2*}	0.088	0.088	0.094	0.094	0.045	0.045	0.132	0.132
Rho	0.581	0.582	0.703	0.704	0.578	0.579	0.657	0.656

Note: With firm-fixed effect. Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity).
P-values in parentheses, significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. R^{2*} reports within group. Rho reports that fraction of variance due to u_i.

Table 1.14 provides the comparison of convergence patterns of the different measures of technology distance, using fixed effects.

The direction and statistical significance of coefficients are consistent for the initially identified technology distance measure (Distance–the highest) and the newly identified measure (top 1 percent).

For the comparison, the estimation results from the initially identified technology distance measures are provided in columns (1) and (2), which is the same as in columns (4) and (5) in table 1.7. The regression results use the new distance measure, which is used frontier firms as average of the top 1 percent TFP firms in Tunisia, in columns (3) and (4).

With top 1 percent distance, the coefficient of tech distance gets slightly larger, and the coefficient of interaction term of tech distance and exports becomes smaller, possibly because of the slightly lower level of frontier and/or the reduced number of observations with the new measure. However, direction and statistical significance of the coefficient of export and tech distance are consistent between columns (1) and (2) and columns (3) and (4).

Also, the comparison between domestic and international distance, using labor productivity, is provided in columns (4) to (8). The results are similar for using domestic distance and international distance, except for the interaction terms, which are insignificant for the domestic frontier, but become negative for the international frontier.

The results of table 1.14 further support the presence of a strong convergence pattern, regardless of which technology distance measure is used. This finding is remarkable since those new distance measures provide smaller magnitude in distance than the initially used distance term (the highest distance and domestic LP are larger than the top 1 percent and international LP distance, on average). However, the export's effect on productivity growth and its interaction effects on technology distance vary depending on which specification is used. The exporter's synergy with technology distance seems to be generated only when the distance is larger. This might imply that when technology distance is smaller, its effect on productivity becomes more important than that of export.

Tables D.9 and D.10 in appendix D provide the same results as table 1.14 above, but by using different econometric techniques, such as OLS and GMM. The results across different distance measures are consistent with the results using OLS methods and similar to the results using GMM, which ensure the estimation results of the tables above. The only difference occurs for the test with the top 5 percent distance in GMM methods, which has much larger and significant coefficients of export and technology distance, but a negative coefficient for the interaction term of the two.

7. Conclusions

Despite rare evidence of productivity convergence, particularly at the firm level, my results confirm that technology distance is a significant factor in explaining productivity growth of firms. In other words, less productive firms catch up to more productive firms over time.

Specifically, there is strong evidence of beta convergence at the firm level, unconditionally and conditionally, which implies less productive firms tend to grow their productivity faster than more productive firms. The estimated technology transfer coefficient, without firm-fixed effects and other controls (unconditional convergence), is about 6.7 percent, which implies that it takes less than eight years for follower firms to eliminate 50 percent of the initial technology gap, regardless of firm-specific characteristics. Moreover, this convergence rate increases to above 12 percent when including firm-fixed effects and other controls (conditional convergence), which is much larger than previous evidence at industry-level.[23] This finding fills the gap in firm-level evidence of the growth and convergence literature.

In addition, in this paper, I link the learning by exporting (LBE) literature to the productivity convergence literature by analyzing its relation to technology transfer.

While previous convergence studies largely examine whether there is convergence or not, they typically do not indicate what leads to the convergence, and specifically, what might potentially contribute technology spillover from more advanced economies to less advanced ones. Unlike previous papers, I present an empirical framework in which technology transfer and exports provide two sources of productivity growth. Using this framework, I evaluate the role of technology transfer and exports in explaining productivity growth at the firm level, for a large sample of more than 11,400 firms in Tunisia from 1997 to 2007. To my knowledge, this is the first paper to examine the role of exporting as a driver of productivity convergence.

My results reveal that the higher productivity level for exporters than non-exporters is explained by self-selection, but not because of learning by exporting. This finding contributes to the ongoing debate in the trade and development economics literature on whether exporter's higher productivity level results from self-selecting into export markets versus learning by exporting.

23. My result of conditional convergence rate above 12 percent is twice larger than Griffith et al. (2004), who used a similar technology transfer term to my specification, but with industry-level data, and much larger than El Arbi Chaffai et al. (2009), who compared Tunisian industries to OECD countries' industries, although it is not possible to directly compare those results with mine.

Moreover, the framework I suggest allows testing exports' effect on productivity growth while controlling for a firm's initial productivity level, relative to the technology frontier, which indirectly controls the potential selection issue of more productive firms becoming exporters, in testing LBE effects. My results reveal that unless initial productivity levels are controlled for, LBE effects will be overestimated.

In addition, my results document that exports play a significant role in determining productivity convergence, and thus growth. The further the distance from the frontier, the greater the potential for technologies to be transferred through exporting; and thus, the higher the rates of productivity growth. The coefficient of interaction terms between exports and technology transfer are positive and statistically significant, implying that while exporters in general do not show faster productivity growth since they are closer to the technology frontier, those far behind the technology frontier grow even faster when they export. This finding that less productive firms will further benefit from exporting could be reflected in export promotion policies in Tunisia.

Remarkably, the results are robust to different specifications and econometric techniques applied to avoid potential measurement error in export variables, collinearity between industry-invariant unobservables and firm-specific characteristics, endogenous export decisions, and different definitions of the technology frontier.

This finding has important policy implications and suggests further research agendas. If the lack of firm entry and exit dynamics prevents firm-level convergence adding up to aggregated convergence of industry, policy should tackle the specific barriers for firm entry and exit. Also, research on identifying barriers that prevent micro-level convergence from adding up to aggregated convergence would be very informative. Meanwhile, for Tunisian manufacturing firms, export promotion will facilitate the less productive firms' catching up with more productive ones over time; thus promoting private sector growth. Promoting FDI will facilitate this catch-up process, but policies that promote innovation, such as subsidies on R&D investment, will not.

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Appendix A — Empirical Evidence on Productivity Convergence

Table A.1 Empirical Evidence on Convergence (Whether or Not There Is Convergence)

Convergence level	Main topic	Findings	Methods/ empirical specification	Data	Authors
Country level	Evidence of convergence	• Evidence of convergence among the US states and across countries, controlling other factors, which is in contrast to the previous findings on negative convergence rate across countries. • Their finding fits the neoclassical growth model with broadly defined capital and a limited role for diminishing returns, and endogenous growth models with constant returns and gradual diffusion of technology across economies. • They also finds that states in which income originates predominantly in sectors that do well at the national level tend to have higher per capita growth rates, i.e., the convergence effect shows up most strongly for manufacturing, but significant effects show up also for six other sectors: construction, mining, services, transportation, wholesale and retail trade, and finance—insurance—real estate. Countries that produce agriculture have a lower income/ convergence rate.	Beta convergence in the neoclassical growth model	Growth of per capita income and product for the 48 US states, 1840-1963, and for 98 countries from 1960-1985	Barro and Sala-i-Martin (1990)
	Human capital	• High-skilled human capital has a positive effect on TFP growth, an effect that is stronger the closer a country is to the technology frontier.	The growth rate of a country is a function of the log of the proximity to the frontier of the previous year, variable of interests, and previous year human capital and their interaction term	A panel of OECD countries	Vandenbussche, Aghion and Méghir (2006)
Industry level	The role of sectors in aggregate convergence How to compare multifactor productivity (MFP) levels across economies	• Manufacturing shows little evidence of either labor productivity or multifactor productivity convergence, while other sectors, especially services, are driving the aggregate convergence result. • Productivity and output per capita differences have narrowed over time. However, the degree of catch-up is less for TFP, suggesting that capital accumulation is playing a role in the convergence of labor productivity. • The paper introduces a new measure of multifactor productivity (TTP) to avoid problems with traditional measures of TFP (coefficient of	Productivity growth is a foundation of the initial productivity level, $\Delta\ln(TFPi) = a + b \ln(TFP,i\ 1970) + e\ i$ (also, used labor productivity) $\Delta\ln(MFPi,t) = \Delta\ln Y\ it - a\ it\ \Delta\ \ln Lit - (1 - a\ it)\ \Delta \ln Ki$, where $ai,t= 0.5(ai,t + ai,t\text{-}1)$ and ait is the labor share of value added in country-sector *i.*	14 OECD countries during 1970-1987.	Bernard and Jones (1996)

		factor inputs do not vary across industries), but their finding using TTP is similar to that with TFP.			
	Focusing on the catching-up process and on the interaction between productivity changes and capital intensity variations	• Contrary to the manufacturing sector and despite very low growth rates, productivity levels converge in services. Moreover, new investments in capital appear to exert an unexpected depressive effect on total factor productivity growth in service activities, while having a positive influence in manufacturing industries.		Service and manufacturing industries, 13 OECD countries, 1970–1987	Gouyette, and Perelman (1997) ** Their finding contrasts with Barro and Sala-i-Martin (1990) and Rodrik (2012)
	Unconditional convergence in manufacturing industries	• The coefficient of unconditional convergence (beta convergence) is large, at between 2 to 3 percent in most specifications. • The paper also finds sigma-convergence at the two-digit level for a smaller sample of countries. • Despite strong convergence within manufacturing, aggregate convergence fails due to the small share of manufacturing employment in low-income countries and the slow pace of industrialization.	Beta convergence: regress the growth of labor productivity in nominal USD on the initial level of labor productivity, a set of industry * time, country FE (or dummies in another specification). A test of unconditional convergence consists of dropping these country dummies and checking whether the estimated coefficient -β remains negative and statistically significant.	More than 100 countries over recent decades UNIDO INDSTAT2 & T4	Rodrik (2012)
	Entry liberalization and privatization	• Entry liberalization and privatization have a positive impact on TFP. • Moreover, this impact appears to be stronger the further away countries are from the technology frontier. • (The interpretation is that entry regulation and public ownership prevents the adoption of existing up-to-date technologies, so that the impact is greater away from the frontier, where TFP growth is more strongly based on adoption rather than on innovation.)	MFP growth equation augmented to account for the impact of product market regulation. Assuming that each industry's MFP growth depends on country and industry characteristics and the state of knowledge in the technology leader country (the highest level of MFP). In particular, an MFP advance in the frontier country is assumed to produce faster MFP growth in follower countries, due to a widening of the production possibility set, with the size of this impact assumed to be increasing with each country's distance from the technological leader. Δ ln MFP =δ (Δ ln MFP Leader) −σ (Technology gap) +β	TFP growth in 18 OECD economies	Nicoletti and Scarpetta (2003) * This result contrasts with the findings in Aghion, et al. (2005)

			Human capital, plus an error term and dummies that control for country-, industry- and time-specific factors not elsewhere accounted for. Note that δ indicates the standard pace of technological transfer from the leader, σ quantifies the importance of the technological transfer that depends on the size of the technology gap, and β shows how the level of human capital affects the pace of technical progress.		
	R&D and absorptive capacity	• R&D has both a direct impact on TFP growth and a role in facilitating the cross-country convergence of TFP levels. • The result is interpreted as providing support for the two "faces" of R&D in promoting productivity growth: on the one hand, R&D enhances a firm's innovative potential (thus increasing directly the rate of TFP growth); on the other hand, it improves the absorptive capacity of firms and industries, thus facilitating the adoption of existing technologies and spurring TFP convergence.	Δ ln Aijt = δ 1 ln(AF/Ai)j t_1 + δ2[(Ri/Yi) ln(AF/Ai)]j t_1 + ρ(Ri/Yi) j t_1 + γXi j t_1 + ψij + T t + εijt	12 OECD countries, two-to-three-digit industry level on value-added, labor and capital stocks, and combined other sources of data for R&D expenditure, skill, and trade	Griffith et al. (2004)
	The effect of FDI inflows on productivity convergence	• A strong convergence effect in productivity, both at the country and at the industry level • FDI inflow plays an important role in accounting for productivity growth • The impact of FDI on productivity depends on the absorptive capacity of recipient countries and industries • Heterogeneity across countries, industries, and time with respect to some of the main findings		Central and Eastern Europe	Bijsterbosch and Kolasa (2010)
	The determinants of the EU–US TFP growth gap, R&D, ICT, and human capital	• TFP growth appears to be driven by catching-up phenomena associated with the gradual adoption of new technologies. • TFP growth is also significantly driven by developments at the “technological frontier,” especially since the mid-1990s. • Industries with higher R&D expenditures and higher adoption rates for ICT-intensive technologies appear to exhibit higher TFP growth rates, while human capital has mostly a significant effect across countries.	TFP growth is a function of TFP growth at the frontier ΔTFPi,j,t = a+b 1ΔTFPL,j,t+ b 2[log(TFPi,j,t−1) − log(TFPL,j,t−1)] +M1Di + M2Dj + M3Dt + εi,j, Measuring TFP is from, Δln AVjt = Δln Vjt − wKjtΔln Kjt − wLjtΔln Ljt while ¯ *wjt* is the two-	10 countries (9 EU countries plus the United States) and 28 industries over the 1980–2004 period, EU KLEMS	McMorrow et al. (2010)

			period average share of the input in nominal value added)		
	Reallocation efficiency accounts for the growth of industry-level productivity	• Industry productivity growth = existing firm productivity growth + the set of firm changes (productive firms enter and less productive firms exit). • The productivity differential between entering and exiting firms accounts for as much as one-half of industry improvement in some industries and time periods		Taiwanese manufacturing sector	Aw et al. (2001)
Firm-level	Technological frontier & market competition & innovation.	• When firms are close to the national technological frontier, product market competition has a stronger positive impact for innovation. • This conclusion can be explained by the observation that being far from the frontier reduced the incentives to innovate by reducing innovators' rents more strongly.	Yij t = α + βEjt + ηi + τt + εij t	UK firms at the US Patents Office, Incumbent UK manufacturing Establishment s, four-digit, 1980–1993	Aghion, Bloom, Blundell, Griffith and Howitt (2005); Howitt and Prantl (2007)
	Summary of different literature using extended Schumpeterian framework	• Important interaction effects between policies and state variables, such as distance to frontier or financial development, in growth regressions.	The extended model typically has LHS as gross output or TFP growth, and RHS includes the distance from technological frontier and its interaction term with the variable of interest		Aghion and Howitt (2006)
	Export/ FDI and productivity	• In their paper, which examines the relationship between exports, foreign direct investment, and firm productivity, they also found that exports and FDI appear to improve firm productivity once the productivity convergence effect is controlled for.	%Δθit = ln θit − ln θit −1 = α + βYit−1 + γChar.sit−1 + εit. In the above regression, they also added the initial TFP level (as variable of convergence) as Japanese firms control variable of convergence, and found a significant negative coefficient		Kimura and Kiyota (2006)
	Analyzing convergence while considering firm entry/ exit effects (selection)	• Convergence rate is much faster among firms (within a country) than cross-country • Without considering the selection, 1.5 percent point downward bias in the speed of convergence. • Productivity convergence, not only in manufacturing, but also in nonmanufacturing, but substantial differences among industries in the convergence speed (e.g., higher technology [IT] industries show faster convergence rate, faster convergence either in growing or slowing down industries — probably because of the leading	TFP is function of catch-up variable (distance to frontier, previous year) and the productivity of previous year. This is rewritten as relative productivity (Tit/Tft) and is a function of relative productivity of the previous year. Then, the selection equation captures the	Japan, both manufacturing industries and nonmanufactu ring firms	Nishimura et al. 2005

		firm's productivity collapse)	effects of exiting decisions of exiting firms (size, age, and ownership type and productivity, etc) using ML function of the sample selection model. TFP is measured as multilateral index method[24].		
	Distance to which frontier?	• The national frontier exerts a stronger pull on domestic firms than does the global frontier • The pull from the global frontier falls with technological distance, while the pull from the national frontier does not. It means that firms far behind the technology frontier might not be able to learn from the global frontier but still benefit from domestic knowledge	Labor productivity (average value added per worker in manufacturing)	UK firms (& other countries as frontiers)	Bartelsman et al. (2008)

Appendix B — TFP Estimation and Variables

At the firm level, TFP is also typically estimated based on a Cobb-Douglas production function, which is an output as a function of the inputs the firm employs and its productivity.[25] Therefore, the measure of TFP obtained is the residual in this functional relationship.

The empirical specification can be written as follows:

$$\ln Y_{ijt} = A_{ijt} + \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \delta_t + \delta_i + \xi_{ijt}$$

- Y_{ijt}: The real output of firm *i* operating in sector *j* at time *t,* which is calculated by the sales revenue deflated by subindustry level deflators from the Producer Price Index (output deflators).
- $\mathrm{K}_{\mathrm{ijt}}$: The value of fixed assets at the beginning of the year, deflated by capital price index, from the National Account.

24. Multilateral index method is based on a hypothetical firm that has the arithmetic mean values of log output, log input; therefore, whether exporting firms gain a productivity increase is an ongoing debate in the trade and development economics literature. To understand the causal effect between exporting and productivity, several techniques have been applied to control the simultaneous effect between productivity and exporting input cost shares over firms in each year. Each firm's output and inputs are measured relative to this hypothetical firm.

25. Cobb Douglas is a restrictive production function because elasticity of substitution between all factors is always 1 (cannot reflect the fact that inputs are either complements or substitutes for each other). This can be addressed by estimating more nonlinear production functions, such as the translog function.

- L_{ijt}: Number of employees.
- M_{ijt}: The value of material inputs adjusted for changes in material inventories, deflated by the output deflators.
- A_{ijt}: The Hicks neutral efficiency level of firm (TFP of firm) measured as the residual of the model/stochastic error term.
- δ_t: Time dummies for 1997–2007.
- δ_i: Firm-fixed effect.
- ξ_{ijt}: Idiosyncratic error, which varies across individual firms.

Output is typically measured as deflated sales or value added. For the LHS, I use gross output (sales revenue) for manufacturing and service industries. I have also considered value added in the LHS. While it is unclear whether value added is a better LHS variable than sales revenue,[26] in my opinion, value added might be preferable in this cross-industry analysis, because when value added is an LHS variable, intermediate inputs ($\ln M_{ijt}$) are no longer required in my RHS (the value added is the revenue minus the materials and indirect costs). Since intermediate inputs might work differently across sectors (for example, between manufacturing and services), not including intermediary inputs in the RHS variables could reduce the potential bias coming from the different ways of measuring intermediate inputs across sectors. However, in the INS data set, there are many missing variables in value-added variables, so the number of observations is significantly diminished by using value added. Therefore, I use revenue as the dependent variable for the entire analysis, but provide comparison of the estimates measured with value added.

The methodological issues estimating firm-level TFP and their solutions

The productivity estimate using ordinary least squares (OLS) could lead to multiple biases, including simultaneity, omitted prices, and omitted variables. Here I summarize some of the issues.

Simultaneity bias (endogenous input selection): If firms have knowledge of their expected productivity, they would choose inputs based on this knowledge; thus there might be correlation between inputs and unobserved productivity shocks, which will result in upward bias in the estimated coefficient.

26. Teal and Soderbom (2005) reported that measurements using value added can generate potential bias, while Brynjolfsson and Hitt (2003) reported that the value-added formulation has the advantage for econometric estimation in that it reduces biases due to the potential endogeneity of materials — the input most likely to undergo rapid adjustment to output shocks.

Econometric techniques, such as parametric 2SLS and GMM, can control endogenous input choice, and therefore overcome the simultaneity bias. I follow the existing literature on using a standard production function approach with different econometric techniques, such as FE and GMM, in addition to OLS. When panel data are available, using a firm-fixed effect method can solve an omitted variable bias problem from time-invariant unobservables (for example, work culture, manager, etc.). For time-variant unobservables (for example, time trends), time dummies can be added in the RHS. In addition, dynamic equations can be estimated by adding lagged dependent variables in the RHS. Also, GMM can be used to avoid the simultaneity bias that can be raised in exporting decisions and endogenous input choice, as well as other omitted variable bias in TFP estimation.[27]

Omitted price bias: TFP is a productivity measure, conceptually based on input quantity versus output quantity. However, most firm-level data do not include information on quantity or firm-level price. If firm-level price variation is correlated with input choice, this will still result in biased input coefficients.

The INS data contain quantity or price information specific to products, but most of the observations are reported as missing values. In the absence of information on prices, the LHS variable is gross output or value added, which is a value term but not a quantity term. This applies to both output and inputs. To deal with the data limitation, I use industry-specific deflators for the value of the outputs (revenue) and inputs (capital and intermediary inputs) to deal with the omitted price bias. In addition, I estimate production functions for each sector to allow the coefficient inputs to vary across sectors.[28]

The deflated values are used as proxies for their quantities, (for example, industry-level price indexes are usually applied to deflate firm-level sales and input expenditures in production function estimates). The output deflator for manufacturing firms is constructed from the INS's Producer Price Index (PPI). For the capital input, I have constructed the deflators from the Gross Fixed Capital Formation of the National Account. For intermediary income, I calculate the deflators based on the input-output table.

27. There are also other ways to measure TFP. One widely used methodology is Olley and Pakes's (1996) semi-parametric 2SLS estimation. However, this methodology cannot be applied to the INS data since there is no information on firm entry and exit in this firm survey. Although I am not using this methodology, I check whether my TFP estimation results are similar to the ones using Olley and Pakes. With Olley and Pakes (as well as Levinsohn and Petrin 2003), the coefficient on L and M should decrease, while the coefficient on K should increase, compared to OLS. De Loecker (2013) made additional extensions of Levinsohn and Petrin by assuming productivity endogenous to export decisions. Also, recent studies have measured productivity in nonstandard ways, using multilateral index (Arnold and Javorcik 2009), two-stage DEA (Simar and Wilson 2011) and Leontief product functions (Hendel and Spiegel 2014).

28. Eberhardt and Teal (2008) explained why it is important to allow for differences in technology as measured by differences in parameters.

However, if firm-level price variation is correlated with input choice, this will result in biased input coefficients since the omitted output price bias will arise if industry-level price deflators are used and if firm-level prices deviate from these deflators (that is, imperfect competition). To deal with this omitted output price bias, I use firm-fixed effects in case a firm has different prices than the others.

Generalized Method of Moments (GMM)

To overcome the abovementioned issues, I have used GMM specifications to measure TFP. GMM can be used to avoid the simultaneity bias in the output-related decision, such as exporting decision, endogenous input choice, and other omitted variable bias in TFP estimation with data with short T and large N. The INS data set has 11 years of time dimension (T = 11, maximum, from 1997 to 2007, but most of the observations have less than 11 years of observations) and a larger firm dimension (N = 1589 for balanced; 12,622 for unbalanced), which is another reason to use GMM.

The abovementioned biases can be raised when input is correlated with error term (A_{ijt}). For instance, when there is exogenous price shock, if material is considered more easily adjustable than labor and capital, then material is more strongly correlated with the error term. Therefore, material is upwardly biased and the other factors are downwardly biased. Instruments can be used to eliminate this bias; however, in general it is hard to find such instruments. Therefore, previous researchers tried to use lagged variables of output and inputs as instruments, which they already have in the firm-level data.

Other productivity measurement — index numbers

It is worth mentioning that much of the convergence literature has used index numbers, which are similar to Total Technological Productivity (TTP), as provided by Bernard and Jones (1996). The details on TTP are well described in their work — but in summary, the strength of this approach is that the specification does not depend on the form of the production function and allows the factor input shares to vary across industries. Also, since it is a relatively simple way of measuring productivity, it is easier to compare the index numbers across countries.

Despite the benefits of index numbers, such as TTP, in my view, there are several advantages in using TFP instead, especially on firm-level data. Index numbers require an assumption on the input share or use the industry average input share across all firms, and therefore do not reflect firm-specific information and could lead to bias. Also, using index numbers would not control the simultaneous bias, which could be caused not only by input influence on output but also by output influence on the input decision. Meanwhile, as with index numbers, by measuring TFP separately by two-digit industry level, I can allow the factor input shares to vary across industries. Therefore, I use TFP by two-digit industry level using recent econometric techniques, such as GMM, which allows the factor input shares to vary across industries while correcting potential simultaneous input selection bias.

TFP growth trend in Tunisia

Tables B.1 and B.2 show the figures of average and standard division of TFP growth by industry over time. The average TFP growth is close to zero for most industries, and standard deviation of TFP growth is very small for most industries. Industry a28 and a33 have relatively high productivity growth, with growth rate about 3 percent on average during the period.

Table B.1 Average TFP Growth

By industry & year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Average
a15	0.02	0.04	-0.03	0.01	-0.02	-0.02	-0.04	-0.05	-0.07	-0.08	-0.02
a16	0.12	-0.09	0.19	-0.12	0.03	0.06	0.12	-0.21	-0.05	0.08	0.01
a17	-0.01	0.00	0.06	0.03	0.07	-0.02	0.05	-0.04	-0.12	-0.03	0.00
a18	0.01	0.01	0.08	-0.02	-0.04	-0.05	-0.02	-0.01	0.00	0.01	0.00
a19	-0.04	0.01	0.03	-0.01	0.01	-0.05	-0.03	0.04	-0.06	-0.02	-0.01
a20	-0.08	0.05	0.07	-0.01	0.02	0.04	-0.11	-0.02	-0.20	0.02	-0.02
a21	0.09	-0.01	0.00	0.01	0.01	0.02	-0.07	0.12	-0.24	0.08	0.00
a22	-0.01	0.03	-0.06	0.03	0.04	0.00	-0.07	0.06	-0.01	-0.08	-0.01
a23	-0.02	0.22	0.09	0.11	0.01	0.06	-0.13	0.20	0.06	-0.38	0.02
a24	-0.10	0.06	0.03	0.01	0.05	0.03	-0.03	-0.08	-0.11	-0.10	-0.02
a25	0.14	-0.02	-0.04	-0.02	0.00	0.02	0.02	0.05	-0.25	-0.16	-0.02
a26	0.00	-0.01	0.00	0.00	0.04	0.04	-0.01	-0.06	-0.02	-0.06	-0.01
a27	0.02	0.06	-0.07	-0.04	-0.12	-0.03	0.00	0.09	-0.06	-0.06	-0.02
a28	0.02	0.01	0.00	0.03	0.04	0.07	-0.09	-0.07	0.16	0.08	0.03
a29	-0.04	0.07	0.03	-0.04	-0.06	-0.17	0.08	-0.10	-0.15	0.10	-0.03
a30				0.35	-0.21			-0.02	-0.10	-0.18	-0.03
a31	0.11	-0.07	-0.10	0.04	0.05	0.02	0.02	-0.02	0.01	-0.03	0.00
a32	0.08	-0.03	-0.31	-0.01	-0.09	0.03	0.22	0.00	0.07	-0.21	-0.02
a33	0.36	-0.01	0.33	-0.17	-0.01	0.07	-0.16	-0.12	0.01	0.02	0.03
a34	0.05	0.00	-0.02	0.04	-0.12	-0.08	-0.03	-0.02	0.09	-0.06	-0.01
a35	-0.55	-0.16	0.06	-0.09	0.05	0.12	-0.11	0.03	-0.09	-0.02	-0.08
a36	0.02	-0.02	-0.02	0.00	-0.02	-0.02	-0.01	-0.06	-0.03	0.01	-0.02

Table B.2 Standard Deviation of TFP Growth within Industry, Over Time

By industry & year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	average
a15	0.02	0.02	0.02	0.02	0.02	0.04	0.05	0.04	0.03	0.05	0.03
a16	0.08	0.10	0.16	0.10	0.07	0.22	0.12	0.22	0.09	0.09	0.12
a17	0.03	0.04	0.04	0.04	0.05	0.06	0.05	0.04	0.06	0.07	0.05

a18	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02
a19	0.04	0.04	0.04	0.06	0.05	0.06	0.04	0.07	0.07	0.08	0.05
a20	0.10	0.06	0.08	0.06	0.10	0.05	0.09	0.08	0.14	0.11	0.09
a21	0.08	0.05	0.05	0.03	0.06	0.04	0.05	0.09	0.04	0.07	0.06
a22	0.08	0.03	0.07	0.05	0.11	0.03	0.04	0.08	0.14	0.11	0.08
a23	0.03	0.18	0.33	0.14	0.04	0.11	0.17	0.16	0.21	0.32	0.17
a24	0.05	0.04	0.05	0.05	0.06	0.07	0.07	0.04	0.05	0.06	0.05
a25	0.06	0.04	0.04	0.11	0.07	0.05	0.08	0.15	0.16	0.06	0.08
a26	0.04	0.04	0.04	0.04	0.03	0.07	0.04	0.05	0.04	0.07	0.05
a27	0.05	0.05	0.04	0.08	0.09	0.09	0.06	0.08	0.07	0.16	0.08
a28	0.04	0.04	0.04	0.04	0.06	0.07	0.06	0.11	0.06	0.08	0.06
a29	0.08	0.07	0.06	0.07	0.06	0.07	0.09	0.09	0.13	0.08	0.08
a30										0.05	0.05
a31	0.09	0.09	0.07	0.08	0.06	0.06	0.08	0.06	0.07	0.12	0.08
a32	0.09	0.13	0.31	0.21	0.17	0.09	0.09	0.09	0.09	0.10	0.14
a33	0.17	0.09	0.13	0.13	0.15	0.10	0.16	0.08	0.10	0.03	0.11
a34	0.05	0.06	0.07	0.06	0.08	0.06	0.06	0.04	0.09	0.07	0.06
a35	0.71	0.08	0.07	0.09	0.10	0.13	0.20	0.18	0.11	0.15	0.18
a36	0.04	0.03	0.04	0.03	0.05	0.06	0.09	0.06	0.05	0.05	0.05

S.D of technology distance (σ-convergence)

Table B.3 shows the actual standard deviation of the (domestic) technology distance variable by industry and year. The standard deviation of the TFP gap is the widely used measurement of σ-convergence in previous literature.

As seen in graph 1.4 in section 3 (Data and Variables), the standard deviation of the technology distance is heterogeneous across industry by year, and there is no clear pattern of this standard deviation decreasing (no evidence of σ-convergence). The standard deviations have been reduced in several industries, such as NACE 16, 22, 30, 33 and 35, implying that firms' distance to top performers becomes somewhat similar to each other; however, in most industries the standard deviation has been sustained.

Table B.3 Standard Deviation of (Domestic) Technology Distance Variable

By industry & year	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
a15	0.03	0.02	0.03	0.03	0.02	0.03	0.05	0.06	0.04	0.04	0.04
a16	0.28	0.22	0.33	0.26	0.13	0.36	0.12	0.02	0.13	0.11	0.19
a17	0.05	0.05	0.05	0.06	0.05	0.06	0.08	0.07	0.06	0.07	0.08
a18	0.03	0.04	0.04	0.03	0.03	0.03	0.04	0.03	0.03	0.04	0.04
a19	0.06	0.06	0.06	0.05	0.06	0.07	0.08	0.07	0.07	0.06	0.08
a20	0.13	0.10	0.13	0.11	0.14	0.16	0.16	0.17	0.19	0.16	0.14

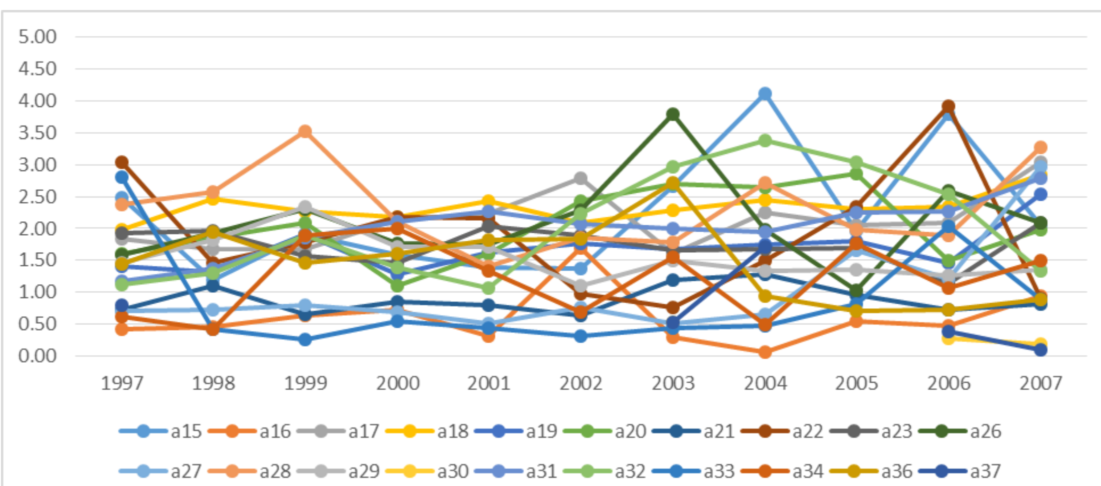
a21	0.08	0.08	0.07	0.09	0.08	0.07	0.10	0.09	0.09	0.09	0.14
a22	0.10	0.07	0.08	0.10	0.09	0.07	0.06	0.12	0.11	0.12	0.07
a23	0.65	0.66	0.56	0.71	0.75	0.71	0.60	0.56	0.58	0.61	0.67
a24	0.13	0.13	0.14	0.13	0.13	0.13	0.19	0.14	0.14	0.18	0.19
a25	0.12	0.14	0.12	0.15	0.12	0.11	0.15	0.12	0.20	0.12	0.15
a26	0.04	0.05	0.05	0.05	0.05	0.06	0.06	0.04	0.04	0.05	0.06
a27	0.08	0.08	0.08	0.08	0.07	0.08	0.09	0.06	0.11	0.09	0.18
a28	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.09	0.08	0.07	0.07
a29	0.11	0.12	0.12	0.11	0.11	0.09	0.13	0.10	0.10	0.11	0.11
a30							0.27			0.14	0.09
a31	0.09	0.08	0.10	0.10	0.11	0.10	0.10	0.10	0.10	0.09	0.12
a32	0.21	0.18	0.22	0.24	0.21	0.28	0.24	0.29	0.21	0.20	0.20
a33	0.43	0.10	0.08	0.14	0.15	0.08	0.07	0.12	0.13	0.19	0.15
a34	0.05	0.04	0.10	0.12	0.10	0.08	0.09	0.06	0.10	0.08	0.10
a35	0.43	0.09	0.06	0.07	0.12	0.16	0.11	0.23	0.11	0.17	0.13
a36	0.04	0.05	0.04	0.04	0.04	0.06	0.06	0.05	0.05	0.04	0.04

Appendix C — Different Measures of Technology Frontier/ Distance

- *Top 1 percent frontier*

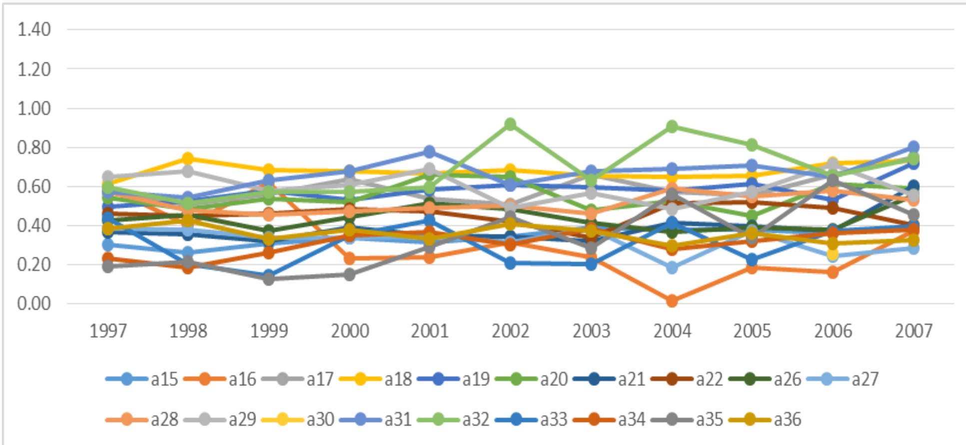
I generate another frontier measure, by taking the average TFP of firms that are at the top 1 percent of TFP level in industry *j* and year *t* (Frontier–top 1 percent). Now the technology distance is a log difference of the frontier 2 and TFP level of an individual firm that belongs to bottom 99 percent of TFP in industry *j* and time *t* (Distance–top 1 percent)

Graph C.1 Top 1 Percent Distance over Time



Note: a24, a25, and a35 are deleted since they are outliers.

Graph C.2 SD of Top 5 Percent Distance



Note: a23, a24, and a25 are deleted since they are outliers, with SD more than 1 in some years.

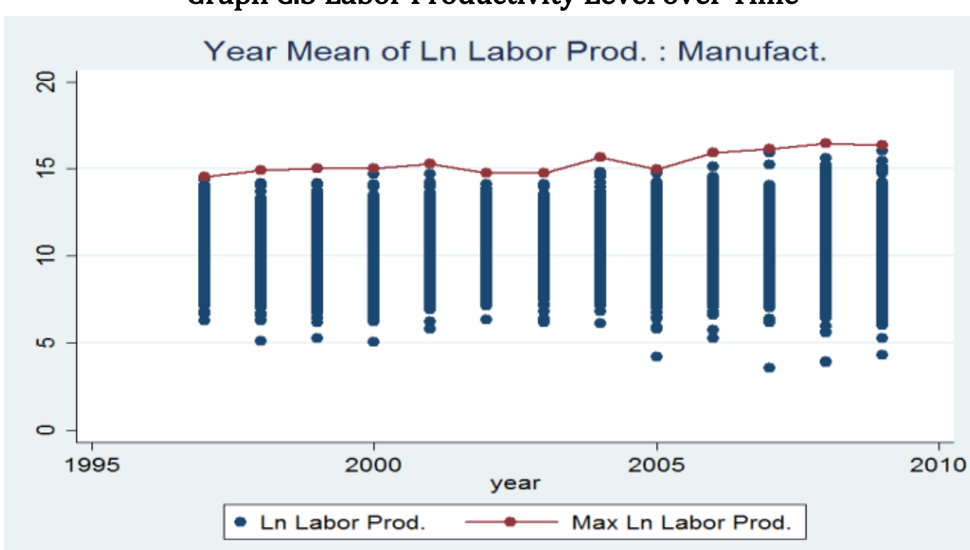
- *International versus domestic frontier, using labor productivity*

I measure labor productivity of Tunisian firms, which is measured by deflated sales revenue, divided by the number of employees.

$$\ln \text{laborprod.} = \ln(real\ revenue) - \ln(employment)$$

Graph C.3 shows the labor productivity trend in Tunisia. The patterns of graph C.3 are similar to graph 1.1 in section 3 (Data and Variables), which shows the TFP level over time. Minor differences include less productive firms that further reduced their productivity level.

Graph C.3 Labor Productivity Level over Time



^*Note:* This figure shows the value of log labor productivity for each firm in manufacturing by year (blue dots), and maximum value for each year.

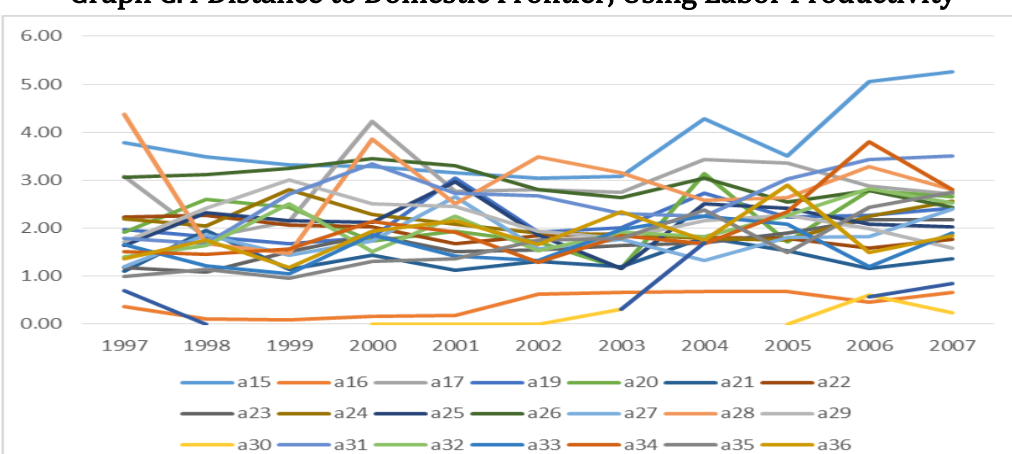
- While only a few frontier firms slightly increased their TFP, and only a few firms far away from the frontier have slightly reduced their TFP level, most firms show similar TFP level over time.
- Compared to using TFP in graph 1.1 in section 3 there might be a few less productive firms that decreased their productivity over time. Although this difference is marginal, it could be explained by those firms that have decreased their output, which is shown as decreased labor productivity, and have invested less in capital inputs during the period of low output. Given that TFP is the residual of the production function, which measures the relationship between inputs and outputs, if a firm reduces its inputs, the residual would decrease less, although output has decreased. This pattern is consistent with the previous literature, which explains that firms that face major changes in output by economic shocks or reduced productivity could adjust their capital inputs more easily than their labor inputs, given the rigidity of labor markets.

Then I measure an additional domestic technology gap using labor productivity of Tunisian firms. The technology frontier is measured by log *c* of the firm with highest labor productivity in industry *i*, time *t*, and the gap is the distance from this technology frontier to the individual firm's log labor productivity in industry *i* and time *t*.

- Domestic frontier, using labor productivity ($L_{DF\ jt}$): a Tunisian firm that has the highest labor productivity in sector *j*, at time *t*

Graph C.4 shows the trend of technology distance to domestic frontier, using log labor productivity.

Graph C.4 Distance to Domestic Frontier, Using Labor Productivity

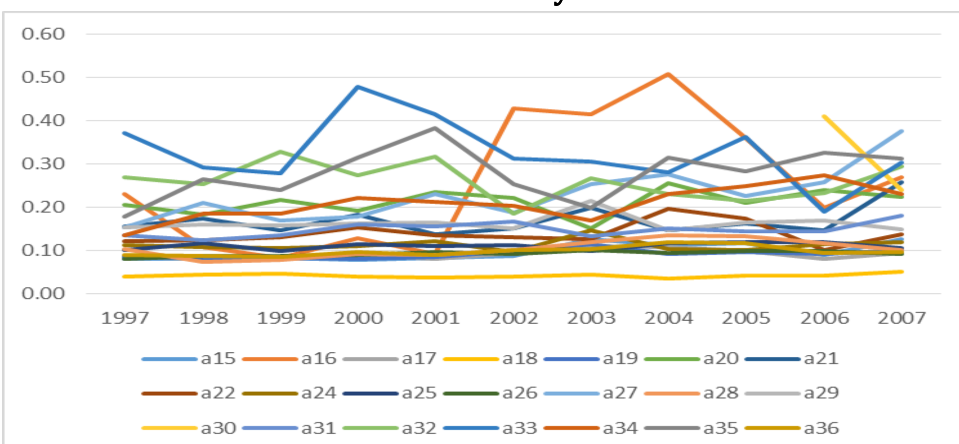


Note: Distance to domestic frontier, using labor productivity that is measured as $\frac{\text{Ln}\left(labor\ Prod_{jt}^{max}\right)}{\text{Ln}\left(labor\ Prod_{ijt}\right)}$; a18 is outlier and deleted.

- Only a few industries are close to the frontier line; the others become slightly further from the frontier line over time. While most industries show a mean industry/ frontier firm ratio in the range of 0.7 to 0.9, some firms are lagging behind.
- In graph C.4, technology distance to domestic frontier (using labor productivity) seems to have been increasing over time, which is different from graph 1.3 (using TFP) in section 3 (Data and Variables), which provides a relatively stagnated distance.

Graph C.5 shows the trend of standard deviation of technology distance to domestic frontier, using log labor productivity

Graph C.5 Standard Deviation of Technology Distance to Domestic Frontier, Using Log Labor Productivity



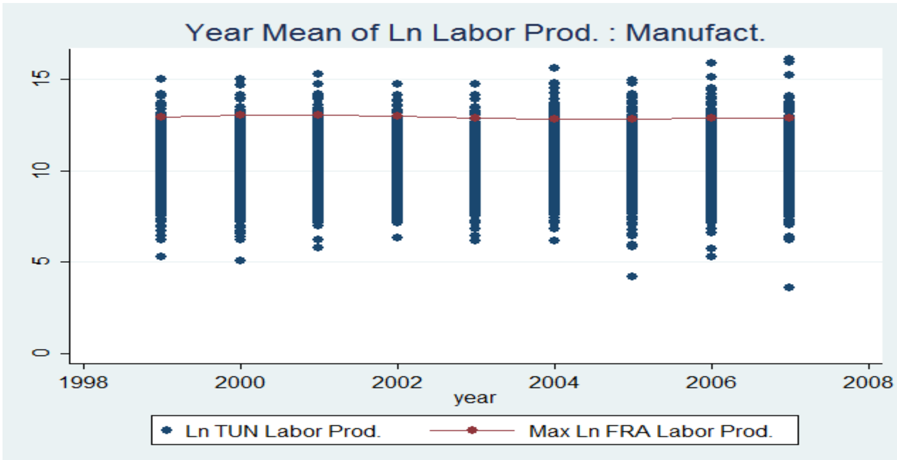
Note: a23 is outlier and deleted.

- Graph C.5 is similar to graph 1.4 in section 3 (Data and Variables), which shows the trend of standard deviation of distance, using TFP. Still, the sigma convergence pattern is not clear.

Then I measure international frontier ($L_{FF\,jt}$), which is French industry-level labor productivity in sector *j,* at time *t.*

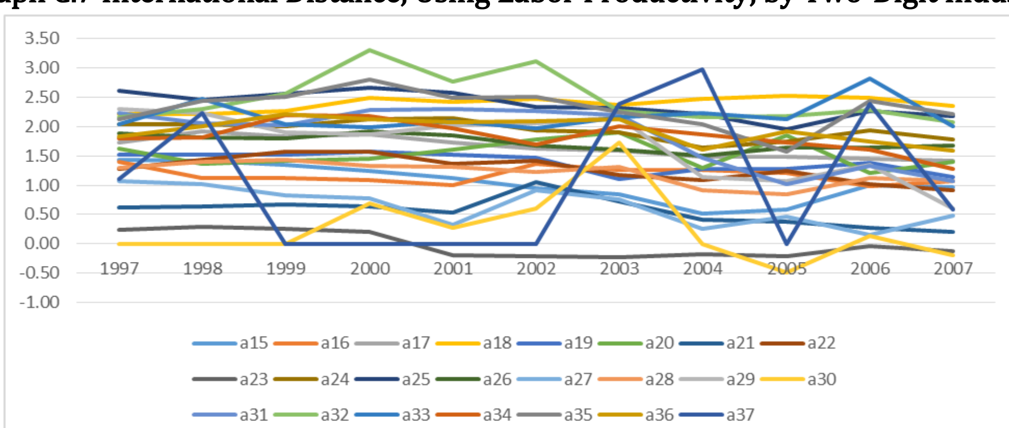
Graph C.6 shows the labor productivity trend for Tunisian firms, which are the blue dots, compared over time to the international frontier ($L_{FF\,jt}$), which is the red line. High-performing firms in Tunisia shows higher labor productivity levels than the international benchmark, the average labor productivity in each industry in France. However, the message and findings from the following graphs are still consistent with the previous results.

Graph C.6 Labor Productivity Level over Time, Compared to International Frontier



- The red line is the French labor productivity average in manufacturing. Without considering industry, top-performing Tunisian firms show higher labor productivity level than the French average.
- When I use international frontier (French industry average labor productivity), high-performing firms in Tunisia show higher labor productivity level than the average French labor productivity.
- However, the message and findings from the following graphs are still consistent with the previous results.

Graph C.7 International Distance, Using Labor Productivity, by Two-Digit Industry

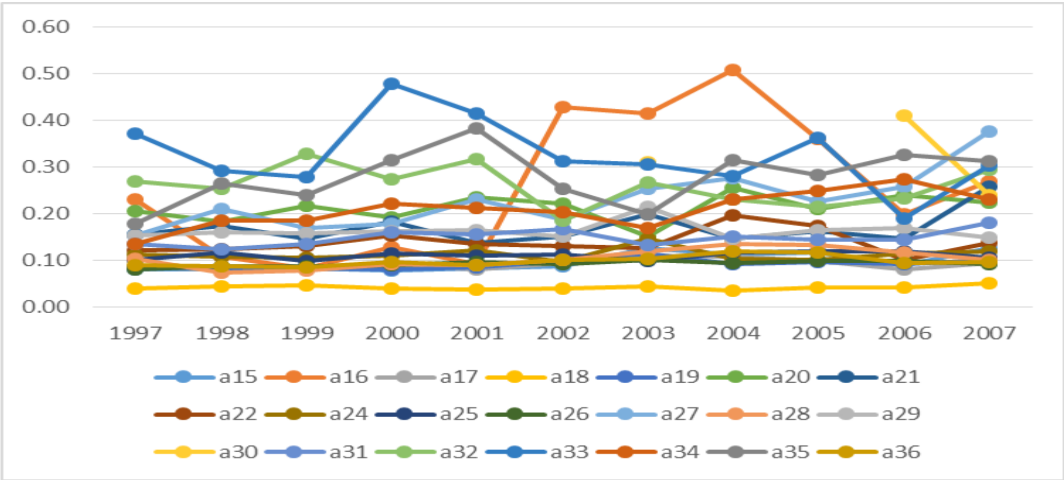


Note: Distance to international frontier, using labor productivity that is measured as $\frac{\ln\left(labor\ Prod_{jt}^{FRA}\right)}{\ln\left(labor\ Prod_{ijt}^{TUN}\right)}$

- International distance, using labor productivity, seems to be slightly decreasing, although it is mostly sustained. This might be caused by the simple fact that the international frontier is lower than the domestic frontier, and so easier to catch up.

- Still, there is large heterogeneity across industries, which is consistent with the previous graph using domestic distance, using TFP (graph 1.3 in section 3, Data and Variables), and using labor productivity (above graph C.4).

Graph C.8 SD of International Distance, Using Labor Productivity



Note: a23 is outliers and deleted.

- Standard deviation (SD) of international distance has been almost sustained and shows very similar pattern with the SD of domestic distance, using TFP (graph 1.4 in section 3, Data and Variables) and using labor productivity (above graph C.5). There is no clear pattern of sigma convergence, occurring in some sectors but not in others.

Appendix D – Additional Results Tables

Openness of frontier firms: tables D.1 to D.4 show whether frontier firms are more open than others, in terms of participating in exports and having foreign ownership. While frontier firms are more likely to receive FDI, the ratio of exporters in frontier firms (50.41) is similar to that in all manufacturing firms (51.36).

Table D.1 Manufacturing Firms' Export Participation in INS Data

Export_stat	Obs.	Percent	Cum.
0	8,013	48.64	48.64
1	8,460	51.36	100.00
Total		16,473	100.00

Table D.2 Frontier Firms' Export Participation

Export_stat	Freq.	Percent	Cum.
0	121	49.59	49.59
1	123	50.41	100.00
Total	244	100.00	

Table D.3 FDI Firms among all Manufacturing Firms in INS Data

FDI_stat	Freq.	Percent	Cum.
0	12,023	72.99	72.99
1	4,450	27.01	100.00
Total	16,473	100.00	

Table D.4 FDI Firms among Frontier Firms

FDI_stat	Freq.	Percent	Cum.
0	147	60.25	60.25
1	97	39.75	100.00
Total	244	100.00	

Table D.5 shows that the suggested IV explains significant variations of export volume as well.

Table D.5 IV2 Export Volume First, Stage

	(1) IV2_OLS	(2) IV2_FE
IV2	3.700***	0.978*
	(0.000)	(0.030)
Constant	-88.486***	-24.956*
	(0.000)	(0.023)
Observations	11,987	11,987
R^2	0.360	0.260

Note: Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity).
P-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table D.6 is essentially the same as table 1.7 in section 6, but using random effects rather than firm-fixed effect. Table D.7 provides Hausman test results that reveal that fixed effect is more appropriate for use in estimating the main specification, equation (1.3).

Table D.6 RE Domestic GAP Export Dummy

	(1)	(2)	(3)	(4)	(5)
	RE	RE	RE	RE	RE

Lag exporter	-0.004		-0.010	-0.095***	-0.100***
	(0.732)		(0.372)	(0.000)	(0.000)
Lag ln (GMM_TFP_Fj/GMM_TFP_ij)		0.110***	0.110***	0.095***	0.096***
		(0.000)	(0.000)	(0.000)	(0.000)
Lag exporter*GMM TFP GAP				0.038***	0.039***
				(0.000)	(0.000)
Lag innovation investment					-0.001
					(0.282)
Lag FDI status					0.030*
					(0.013)
Constant	-0.008	-0.336***	-0.338***	-0.296***	-0.294***
	(0.657)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11,428	11,428	11,428	11,428	11,428
R^2					
r2_o	0.002	0.047	0.047	0.048	0.048
Rho	0.102	0.118	0.118	0.121	0.120

P-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; to perform the Hausman test, it is not allowed to cluster standard error.

Table D.7 Hausman Tests Results

Column	*P*-value: difference in coefficients not systematic	Suggested model
1	0.000	FE
2	0.000	FE
3	0.000	FE
4	0.000	FE
5	0.000	FE

Hausman test compares an estimator θ1 known to be consistent with an estimator θ2 that is efficient under the assumption being tested. The null hypothesis is that the estimator θ2 is indeed an efficient (and consistent) estimator of the true parameters. If this is the case, there should be no systematic difference between the two estimators. If there is a systematic difference in the estimates, you have reason to doubt the assumptions on which the efficient estimator is based. The Hausman test can also differentiate between a fixed-effects model and a random effects model in panel data. In this case, random effects (RE) is preferred if the null hypothesis cannot be rejected due to higher efficiency; otherwise, fixed effects (FE) is at least consistent and thus preferred.

Fixed effects should be chosen, based on the results from comparing FE versus RE models.

Table D.8 provides the second-stage regression results with predicted value of export volume using different instruments. The results are consistent with those in table 1.13 in section 6.

Table D.8 Different Econometric Techniques — IV 2SLS with Export Volume

Dep. var. = TFP growth	(1) IV2 OLS	(2) IV2 OLS	(3) IV2 Panel	(4) IV2 Panel
Lag exporter	0.004^{***}	0.003^{***}	-0.024^{**}	-0.020^{**}
	(0.001)	(0.001)	(0.003)	(0.003)
Tech distance	0.052^{***}	0.051^{***}	0.048^{***}	0.049^{***}
(Lag Ln TFP_Fj/TFP_ij)	(0.000)	(0.000)	(0.001)	(0.001)
Lag exporter × tech distance	0.007^{***}	0.007^{***}	0.020^{***}	0.020^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Lag innovation investment		-0.001		-0.002
		(0.223)		(0.054)
Lag FDI status		0.032^{**}		-0.017
		(0.002)		(0.024)
Constant	-0.090	-0.085	-0.348	0.038
	(0.066)	(0.090)	(0.248)	(0.900)
Observations	11,422	11,422	11,422	11,422
R^2	0.053	0.054	0.010	0.011
Rho*	n.a.	n.a.	0.600	0.600
Test regression – Coeff. of IV on the residual of second stage	-0.005^{***}	-0.005^{***}	0.162^{***}	0.175^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
R^2 of the test regression**	0.001	0.001	0.068	0.079

Note: Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity) and corrected, n.a. = not applicable.

P-values in parentheses, significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, R^2 is reported but it is not important in 2SLS. * Rho is fraction of variance due to u_i. ** R^2 of the test regression is from the OLS of IV on residual of second stage regression.

Columns (1) and (2) provide the estimation results using OLS, and columns (3) and (4) provide the results using firm-fixed effects. The results are very similar to table D.9.

Instrumenting initial export volume reduces the estimated coefficient of technology transfer to between 4.8 percent and 5.2 percent in columns (1) to (4). The coefficient of the interaction term between previous export status and technology gap is in the range between 0.7 percent to 2.0 percent and statistically significant. As in table D.9, the coefficients get larger with firm-fixed effects, as shown in columns (3) and (4). Meanwhile, the estimated coefficient of export status shows mixed results, and becomes negative in columns (3) and (4).

In columns (1) and (2), the coefficients of IV on the residual are statistically significant but small, and R^2 of test regression is close to zero, which ensures that the suggested instrument is not correlated with the residual of the primary instrument (instrument is valid). Again, the results using firm-fixed effects, in columns (3) and (4), require careful interpretation, with a larger coefficient of IV and R^2 in the test regression. Corrected standard error becomes smaller in columns (1) to (4) as expected.

Tables D.9 and D.10 provide the test results for the different distance, but by using different econometric techniques, such as OLS and GMM. The results with different distance measures are consistent across different econometric techniques, which ensure the estimation results of the table 1.14 in section 6.

The only difference occurs for the test with the top 1 percent distance in GMM methods, which has much larger and significant coefficients of export and technology distance, but a negative coefficient for the interaction term of the two.

While the magnitude and direction of coefficients are similar for other distance measures, there are major changes in coefficients when I test the top 1 percent distance in columns (3) and (4) of table D.9. The coefficients of convergence become much larger for the distance with top 1 percent TFP. The coefficient of export become significant and positive, while the coefficient of the interaction term between export and technology distance becomes negative and statistically significant.

Table D.9 Comparisons of Different Distance — OLS, Lag Export Dummy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep var = TFP growth	Domestic TFP -The highest	Domestic TFP -The highest	Domestic TFP – Top 1%	Domestic TFP – Top 1%	Domestic LP	Domestic LP	Intl LP	Intl LP
Lag exporter	-0.062***	-0.070***	-0.031	-0.041	-0.002	-0.008	-0.002	-0.007
	(0.001)	(0.000)	(0.196)	(0.097)	(0.887)	(0.659)	(0.904)	(0.653)
Tech distance (Lag ln TFP_Fj/TFP_ij	0.085***	0.085***	0.084***	0.084***				
	(0.000)	(0.000)	(0.000)	(0.000)				

)								
Dom. LP distance (TUN LP_Fj/LP_ij)					0.041***	0.042***		
					(0.000)	(0.000)		
Int. LP distance (FRA LP_Fj/LP_ij)							0.062***	0.064***
							(0.000)	(0.000)
Lag exporter × tech transfer	0.025***	0.026***	0.011	0.012				
	(0.000)	(0.000)	(0.307)	(0.279)				
Lag exporter× TUN labor prod GAP					0.002	0.002		
					(0.641)	(0.645)		
Lag exporter× FRA labor prod GAP							0.009	0.008
							(0.214)	(0.287)
Lag innovation investment		-0.001		-0.000		0.001		0.001
		(0.486)		(0.715)		(0.206)		(0.102)
Lag FDI status		0.030**		0.035***		0.014		0.019
		(0.004)		(0.000)		(0.185)		(0.066)
Constant	-0.260***	-0.261***	-0.156***	-0.157***	-0.147***	-0.157***	-0.060***	-0.073***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Observations	11,428	11,428	9,564	9,196	11,428	11,428	11,428	11,428
R^2	0.048	0.049	0.038	0.044	0.015	0.015	0.025	0.025

Note: Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity).
P-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table D.10 GMM + Lag Export Dummy

	(1) Domestic TFP -the highest	(2) Domestic TFP-the highest	(3) Domestic TFP -top 1%	(4) Domestic TFP-top 1%	(5) Domestic LP	(6) Domestic LP	(7) Intl LP	(8) Intl LP
Lag exporter	-0.266*	-0.276*	0.354	0.326	-0.114	-0.134	-0.048	-0.058
	(0.047)	(0.045)	(0.074)	(0.088)	(0.295)	(0.241)	(0.621)	(0.555)

Tech transfer (Lag ln TFP_Fj/TFP_ij)	0.081***	0.080***	0.740***	0.725***				
	(0.000)	(0.000)	(0.001)	(0.001)				
Lag ln (TUN LP_Fj/LP_ij)					0.047**	0.045**		
					(0.002)	(0.003)		
Lag ln (FRA LP_Fj/LP_ij)							0.101***	0.101***
							(0.000)	(0.000)
Lag exporter × tech transfer	0.094*	0.096*	-0.186*	-0.187 *				
	(0.033)	(0.031)	(0.034)	(0.031)				
Lag exporter × TUN labor prod GAP					0.023	0.027		
					(0.388)	(0.325)		
Lag exporter × FRA labor prod GAP							0.023	0.025
							(0.569)	(0.536)
Lag innovation investment		-0.001		-0.017***		0.001		0.001
		(0.207)		(0.001)		(0.608)		(0.392)
Lag FDI status		0.029		0.316***		0.016		0.020
		(0.116)		(0.001)		(0.342)		(0.213)
Constant	-0.259***	-0.268***	-4.364***	-4.009*	-0.165**	-0.148*	-0.090*	-0.107*
	(0.000)	(0.000)	(0.000)	(0.002)	(0.003)	(0.025)	(0.011)	(0.024)
Observations	11,428	11,428	9,564	9,564	11,428	11,428	11,428	11,428
AR2	2.117	2.101	-2.43	-2.48	2.269	2.276	2.277	2.273
AR2 (*p*-value)	0.034	0.036	0.015	0.013	0.023	0.023	0.023	0.023
Sargan/Hansen (*p*)	0.004	0.004	0.557	0.586	0.000	0.000	0.001	0.001
Diff. in Hansen (*p*)	0.604	0.608	0.617	0.628	0.717	0.550	0.957	0.965

Note: With firm-fixed effect. Year and industry dummies were included but not reported.

Nondynamic system GMM with lag 2 and 3. The instrument set for the differenced equation consists of the log of TFP growth, lagged export status, in levels, in periods $t-2$ and $t-3$ (among which the missing values are treated as 0 and the instruments for each period are collapsed), and the gap variable, interaction between gap and previous year export, year and industry dummies, differenced. The instrument set for the levels equation consists of the log of TFP growth, lagged export status, the gap variable, interaction between gap and previous year export, a constant, and year and industry dummies.

P-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.