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ORIGINAL PAPER

Industrial structure and total factor productivity: the Tunisian manufacturing sector between 1998 and 2004

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Abstract Using a panel of manufacturing firms operating in 138 delegations across the Tunisian coast and observed over the 1998–2004 period, we study the impact of industrial structure on regional economic growth measured by total factor productivity. The results of an unbalanced panel data-based model indicate that the diversity of the industrial scene seems to be a local growth-promoting factor for high-tech sectors. Specialization often articulates the impact of diversity, while competition positively affects productivity.

JEL Classification C33 · D24 · O10 · R11 · R12

1 Introduction

Since the mid-1980s, Tunisia has adhered to a set of economic reform programs mainly the adoption of a structural adjustment program in 1986, update level in 1995 and the Association Agreement with the European Union for the gradual establishment of a free trade agreement. The main objective of these reforms is to put the national economy on a path of high growth in a monetary stability environment and expand areas of competition in order to ensure better competitiveness of the productive system by reinforcing the potential of firm's performance. These reforms have resulted in the restoration of macroeconomic stability, and growth is enhanced through increasing contribution of total factor productivity.

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Although this opening gave results in terms of economic growth, it created a geographical polarization favoring coastal areas that contain most urban agglomeration (El Bekri 2000; Dlala 1999; Belhedi 1993). Coastal areas are the most favored axis by investors. They have attracted more than 75 % despite a redistribution effort since the 6th Plan of 1977–1981. More than 90 % of the total employment is still generated in the coastal part of the country, which concentrates 65 % of urban areas (Dlala 1997). It ensures 90 % of the industrial added value, 83 % of the motor industry and 66 % of modern industry. Despite the efforts made by the state in terms of conditions for investment attractiveness and incentives accorded to enterprises located in the interior regions, coastal areas remain the most attractive and most privileged territory for local and foreign enterprises.

The coastal development of industrial activity in Tunisia is obviously a source of externalities supported by spatial agglomeration forces, which is not without consequences on productivity. The extent and manner in which the productive performance of Tunisian firms is affected by these agglomeration forces is one of the major contributions of this paper.

Generally people tend to move in areas where productivity is higher in order to enjoy higher living standards.[1] Thus, productivity difference can be strengthened by the fact that workers and firms can move toward the most productive areas leading to increased incomes and employment in the regions that experience high productivity. Firms and workers are substantially more productive in large and dense urban environments where the vast majority of substantial innovations emerge (Puga 2010). The productivity advantages of cities and urban clusters with a high density of firms and workers have received much attention by the urban economists for a long time. Martin et al. (2011) stress the importance of analyzing the agglomeration economies to better understand the economic mechanisms at work at the local level besides its potentially important policy implications.[2] Traditionally, agglomeration economies represent the comparative advantages in terms of productivity that provides to a firm or group of firms one region over another, because of its size and structure. So from a policy perspective, it is judicious to consider how large are the gains from agglomeration and how much do firms internalize these gains when deciding where to locate?

In this context, some studies attempted to explain and identify geographical and appeal factors that determine local development of a given region in Tunisia. Metral (2003) identified geographical and appeal factors of Tunis city for industrial companies. He concluded that consideration of entrepreneurs' motivations is likely to explain the presence of concentration and dispersion mechanisms around the capital. Driss (2007) tried to evaluate the effect of some macroeconomic variables such as market size, labor availability and free trade agreements over the geographical loca-

[1] Puga (2010) stress that the underlying reason to look hard at agglomeration economies in production is that if agglomeration increases productivity, then it can potentially increase earnings, income and standards of living. Krugman (2005) explains, when we consider countries, a 5 % difference in productivity will translate into (roughly) a 5 % difference in living standards.

[2] Agglomeration economies have been used to justify cluster policies by national and local governments in many country such as Germany, Brazil, Japan, Southern Korea, Spanish Basque country or more recently France (Martin et al. 2011)

tion of foreign industrial firms in Tunisia. Examining five industrial sectors in 138 delegations across the Tunisian coast observed during the 1998–2004 period, Amara and Thabet (2012) studied the impact of industrial structure, wages and foreign direct investments on the production of manufacturing companies. They did not reject the role of agglomerations in regional growth in Tunisia.

This paper aims to study the impact of agglomeration and dispersion mechanisms related to industrial structure and economic size on total factor productivity. The sample consists of Tunisian firms belonging to seven manufacturing sectors in 138 delegations across the Tunisian coast observed over the 1998–2004 period. We use as a measure of regional development "total factor productivity" (TFP) by sector instead of the employment by sector. This choice is justified by the fact that productivity of a firm may increase without a parallel increase in employment, which is true in the case of a strong substitution between capital and labor (Baudewyns 2005). TFP is calculated through an econometric estimation of a production function following Olley and Pakes (1996)' approach, which corrects simultaneity bias due to an instantaneous correlation between unobservable productivity shocks and production factors.[3] In this study, we use the administrative unit of "delegation." Using governorate-based data may hide strong heterogeneity (labor and other variables used in the model) between the different delegations of the same administrative unit (the governorate). To our knowledge, these issues have never been addressed in Tunisia under a microeconomic panel data analysis with very detailed data.

The remainder of this paper is organized as follows. Section 1 summarizes the different theories and some empirical studies on determinant of spatial agglomeration and local growth. In Sect. 2, we present the empirical model, the variables used in the model and the total factor productivity estimation. The data set and the results are provided and interpreted in Sect. 3, while Sect. 4 concludes with some final observations and policy implications.

1.1 Agglomeration economies, externalities and regional growth: a theoretical and empirical survey

Empirical studies of the relationship between specialized versus diversified spatial agglomeration and their growth dates back to the 1990s with the pioneering work of Glaeser et al. (1992) and Henderson et al. (1995). These studies focused on the relationship between the growth of the operating sectors of a local economy, measured by employment growth, and the externalities associated with agglomeration economies. Glaeser et al. (1992) distinguish three types of agglomeration externalities: MAR (Marshall–Arrow–Romer), Porter and Jacobs externalities. Marshall (1980) argued that industries tend to specialize geographically because the proximity facilitates transmission of intra-industry knowledge, reduces transport costs of inputs and outputs and allows firms to benefit from a more efficient labor market. On the other hand, Marshall (1980), Arrow (1962) and Romer (1990) claimed that agglomeration externalities operate within an industry and arise from local concentration of that

[3] Olley and Pakes (1996).

industry. These scale externalities are called localization economies, or in a dynamic context, Marshall–Arrow–Romer (MAR) externalities. They focused on knowledge spillovers between firms in the same sector. In fact, the firms agglomeration of the same industry produce positive externalities and facilitate the growth of all manufacturing units within the sector. Accordingly, local industrial specialization would be an effective way to increase positive externalities between firms. Thus, the growth process would be enhanced. Moreover, specialization promotes technological spillovers and facilitates the access to specialized and sector-specific practices. Marshall mentioned also that labor market pooling in the same region promotes economies of scale through the sharing of labor equipment and infrastructure. In Marshallian tradition, MAR externalities can be attributed to three sources (Neffke et al. 2011): labor market pooling, input–output linkages and intra-industry knowledge spillovers.

In contrast, if the variety of both local industrial environment and competition contributes to a faster adoption of knowledge, externalities are called externalities of urbanization or, in a dynamic context, Jacobs' (1969) externalities (Batisse 2002a, b; Henderson 2003). Contrary to Marshall who supports the urban specialization, Jacobs stresses the importance of urban diversity. According to these authors, local diversification within an urban region fosters innovation and result in cross-fertilization of ideas which in turn favors economic growth. Consequently, variety and diversity of industries within the same geographical area promote innovation and growth.

Porter (1990) argued that technological externalities essentially develop within the same industry and that specialization is good for growth, jointly for the industry itself and the agglomeration wherein it is located. Porter also assumed that local competition between firms positively affects growth. It feeds innovation and encourages firms to invent new ideas. In this view, for any given set of industrial clusters, competitive pressure enhances productivity. Indeed, local competition facilitates innovation and supports the creation of new ideas. It can increase the productivity of firms and stimulate the formation of new businesses within the area.

Among the recent empirical studies of the effect of agglomeration economies on local growth in developed countries,[4] we mention those of Combes (2000) and Martin et al. (2011) for France, Suedekum and Blien (2007) for Germany, Baudewyns (2005) for Belgium, Batisse (2002a, b) for 29 Chinese provinces (Martin et al. 2011). The majority of those studies evidenced positive externalities arising from urban or industrial scales. It is difficult to compare results pointed out by several studies because the applied econometric approaches were based on a variety of estimation strategies using different dependent variables (Graham and Kim 2008). Using American data, Glaeser et al. (1992) found that sectoral employment growth at local level is negatively affected by specialization. On the contrary, industrial diversity seems to favor sectoral employment growth. In contrast, Henderson et al. (1995) showed that mature industries tend to be subject to localization economies, but not to urbanization externalities, whereas high-tech industries are subject to both economies. For 341 employment areas observed over the period of 1984–1998, Combes (2000) also found out a negative effect of specialization and diversity on employment growth in the industry and service in

[4] For recent reviews of the empirical literature, see Rosenthal and Strange (2004) and Graham and Kim (2008).

France. Batisse (2002a, b) provided empirical evidence about the relation between the local economic structure (local sectoral specialization, diversity and competition) and the 1988–1994 value-added growth of Chinese provinces. The econometric analysis shows that while diversity and competition have a positive influence on local growth, specialization has reversely a negative impact. Suedekum and Blien (2007) estimated that on dynamic panel data the regression of employment growth using 15 manufacturing industries from 26 German districts observed over the period of 1980–2001. The results evidenced that employment growth is solely promoted by diversity.

Therefore, a lot of studies based on employment growth do not confirm the existence of Marshallian externalities and even tend to show a negative impact of specialization on employment growth, whereas evidence about urbanization economies is rather mixed. As productivity contributes importantly to economic growth, research in this field is then shifted to examining the effect of agglomeration economies on firm productivity, using firm-level data. The seminal work by Henderson (2003) and Cingano and Schivardi (2004) is those of the first empirical studies of the effects of agglomeration economies on firm-level productivity growth. Using firm-level-based TFP indicators, Cingano and Schivardi (2004) estimate the effects of alternative sources of dynamic externalities at the local level. The author find that industrial specialization and scale indicators affect TFP growth positively, while neither product variety nor the degree of local competition has any effect.

For developing countries, there are very few studies dealing with agglomeration economies and their impact on growth using microeconomic panel data. In spite of this scarcity, we notice a mixture of studies and research designs. Bun and Makhloufi (2007), for instance, use a panel of 95 geographical areas of six Moroccan regions (Casablanca, Rabat, Tangier, Fes, Meknes and Marrakech) observed from 1985 to 1995 in order to study the effect of agglomeration economies on local economic growth. Examining 18 manufacturing sectors, the obtained results indicate that local employment growth positively depends on MAR and Jacobs externalities. Catin et al. (2007) confirm the results found by Bun and Makhloufi (2007), using data on Moroccan provinces over the period of 1985–1999.

Cota (2002) attempted to investigate the effect of agglomeration economies on the manufacturing sector of the northern border cities of Mexico. An econometric model was established to relate agglomeration with manufacturing growth. The results show that the externalities caused by industrial specialization among industries make up one of the explicative factors of manufacturing employment growth during 1988–1993. Matlaba et al. (2012) employed the Glaeser et al. (1992) approach to identify the role played by knowledge externalities in manufacturing employment growth and convergence across 26 states of Brazil. They found diverse results depending on the model specification. The results provide new insights into the rapid growth since 1981, particularly the north and center west of Brazil. Widodo et al. (2014) examined the effect of agglomeration economies on productivity growth in Indonesian manufacturing industries. They found evidence of a positive specialization effect and a negative diversity effect for aggregate manufacturing and sub-sectors. Furthermore, the competition index has mixed effects across industries; Porter's competition externalities stimulate firm productivity growth solely under some conditions.

One thing still seems to emerge from the empirical literature on developing countries. It seems that Jacob's externalities and Porter's are confirmed more in the case of economies located at a certain stage of development, while MAR externalities are confirmed in the case of less developed economies (Beaudry and Schiffauerova 2009). In addition, the empirical investigation involving firm-level productivity have not been quite abundant in developing countries and more specifically in Tunisia.[5] While these empirical studies have provided interesting results, it largely focuses on firm's characteristics regardless of their location and ignoring the effects that spatial agglomeration plays on productivity at firm and industry level. This issue has received little attention and has remained relatively unexamined and poorly understood despite its important implication on productivity growth in Tunisia. In this paper, we try to overcome this shortcoming by considering the issue of knowledge spillovers through local externalities to analyze the determinants of firm-level productivity.

2 Model and definition of variables

2.1 The empirical model

Empirical studies on the relationship between externalities and firm's performance have been an important development since the work of Glaeser et al. (1992) and Henderson et al. (1995). These authors focused on the relationship between local economic growth, as measured by employment growth in a given geographical area, and a set of indicators specifying the role of specialization, diversity and competition. The majority of studies that followed these two papers have often found evidence of positive externalities arising from urban or industrial scale, while the impact of specialization is, in most cases, not significant (for a review of the empirical literature, see Rosenthal and Strange 2004; Graham and Kim 2008). Cingano and Schivardi (2004) related these results to the fact that technological spillovers affect productivity rather than employment. Moreover, inferring productivity through employment is often problematic. Combes et al. (2004) showed that for a positive productivity shock to yield employment growth, demand should be elastic enough. To solve this problem, like Henderson (2003) and Cingano and Schivardi (2004), Baudewyns (2005), and more recently Martin et al. (2011), we use total factor productivity as a measure of regional development rather than employment.

The literature proposes two estimation strategies of agglomeration externalities from individual firm data.

The first strategy, in one step, directly involves the introduction of agglomeration indicators and inputs in the production function. In fact, the literature on agglomeration economies clearly suggests that agglomeration-related variables affect the firm's production activity (Rosenthal and Strange 2004). Thus, the production function is estimated as a function of labor and capital as well as agglomeration variables (see,

[5] As an example, we mention Baccouche et al. (2008) who propose to study the impact of FDI on TFP from a panel of Tunisian manufacturing firms over the period of 1998–2004 and Baccouche and Kouki (2003) and Goaied and Mouelhi (2000) who proposed to estimate the firm-level technical efficiency and to decompose the TFP growth in Tunisian textile, clothing and leather industries during the period of 1983–1994.

for example, Graham and Kim 2008, for a good discussion). Using 3000 firms, Henderson (2003) implements this strategy. The unobservable individual heterogeneity is controlled by the introduction in the model of an individual fixed effect and thus eliminate the bias that would result from the omission of certain variables. This strategy poses several challenges. With a large amount of data, the joint estimation of technological coefficients at sector level and individual fixed effects is difficult to implement. Identification then rests on inter-temporal variations that are very low for urbanization variables. Finally, if agglomeration externalities contribute in part to the individual fixed effect, estimates may be biased (Barbesol and Briant 2008).

The second strategy seeks, in the first step to build an indicator of local sectoral productivity from estimating the individual productivity of each firm. The second step consists to regress this local sectoral productivity on agglomeration variables. This strategy has the advantage of greater flexibility in the first step of estimating the production function; however, this procedure suffers from two serious shortcomings. First, the existing TFP measure is biased because it leaves out the effect of agglomeration variables. Second, the estimation of the TFP regression at the second step is likely to be misspecified because, in general, the input levels (labor and capital) also affect TFP. In this paper, we favor the second strategies while introducing, in the second regression, the level of inputs as well as agglomeration variables.

The to-be-estimated model is written as follows:

$$\begin{aligned}\log(pgf_{sdt}) = {} & \alpha_{sd} + \beta_1 \log(sp_{sdt}) + \beta_2 \log(conc_{sdt}) + \beta_3 \log(div_{sdt}) \\ & + \beta_4 \log(size_{sdt}) + \beta_5 FDI_{sdt} + \beta_6 \log(RD_{sdt}) \\ & + \beta_7 \log(capital_{sdt}) + \beta_8 \log(labor_{sdt}) + \mu_{sdt} \\ s = {} & 1, \ldots 7; d = 1, \ldots 138 \end{aligned} \tag{1}$$

where pgf_{sdt} denotes total factor productivity of sector s in delegation d observed at time t; sp, $conc$, div, $size$, FDI, RD, $capital$ and $labor$ are, respectively, the variables specialization, competition, diversity, firm size, foreign direct investments, research and development allocations, capital and number of employees. μ_{sdt} is a classic error term specific to any econometric model and α_{sd} denotes an individual specific effect, which allows for controlling unobservable heterogeneity.

2.2 The construction of variables

2.2.1 Specialization

According to specialization hypothesis, interaction of firms in the same sector promotes accumulation and diffusion of knowledge, training, and facilitates innovation in the concentrated industry within the region through intra-sector spillovers. These advantages, which are inter-firms and intra-sector, are called MAR-type externalities.

Note that several indices have been proposed in the literature to identify the effects of localization economies like the share of a region's production in an industry, the number of firms by sector in a region, the proportion of employees in a region, several indices based on technological closeness of sectors, measures indicating the share of own industry in a region (measured either by output, R&D investment or industry value added) and so on.

The location quotient and the industrial employment represent the two most common indicators of externalities Marshall used in literature (Beaudry and Schiffauerova 2009). Glaeser et al. (1992) suggest that the degree of specialization can better represent the Marshall externalities than the size of the industry as it better capture the density and intensity of the interaction between firms. The location quotient represents the fraction of employment or added value in a region to the national share. However, in some cases a simple location quotient, as the share of a region's employment or value added in an industry, is used to measure externalities MAR. Nevertheless, the relative indicator of specialization has the advantage to take into account the size of industries at the national level, whereas the simpler indicator does not. Thus, according to Batisse (2002a, b), in this paper, we retain as a measure of specialization the location quotient calculated with value added given by:

$$sp_{sd} = \frac{VA_{sd}/VA_d}{VA_{sl}/VA_l}$$

if sp_{sd} is greater than 1, then delegation d has high concentration of the value added generating in sector s. The greater the Knowledge of spillovers in the sector, the higher is the specialization index.

2.2.2 Competition

Like Combes (2000) and Catin et al. (2007), we define competition index of a sector s in delegation d as the opposite of Herfindhal's concentration index, established as a function of the weight of each firm in each delegation. The competition variable is defined as follows:

$$comp_{sd} = \frac{1\Big/\sum_{i\in s,d}\left(\frac{VA_i}{VA_{sd}}\right)^2}{1\Big/\sum_{i\in s,l}\left(\frac{VA_i}{VA_{sl}}\right)^2}$$

where VA_i VA_{sd} and VA_{sl} are, respectively, the added value of firm i, the value added of sector s in delegation d and that of the sector s in coastal area l. A positive sign of the competition coefficient indicates its contribution to productivity gains, while a negative sign indicates that a monopole context is preferable for the sector under examination.

2.2.3 Diversity

Referring to the work of De Lucio et al. (2002), Batisse (2002a, b) and Catin et al. (2007), we use as a measure of diversity the opposite of Herfindhal's sectoral competition index computed over the set of sectors except for the examined sector, standardized by the same index computed on coastal areas.[6]

$$div_{sd} = \frac{1\Big/\sum_{s' \neq s}^{S}\left(\frac{VA_{s'd}}{VA_d - VA_{sd}}\right)^2}{1\Big/\sum_{s' \neq s}^{S}\left(\frac{VA_{s'l}}{VA_l - VA_{sl}}\right)^2}$$

This variable allows us to identify possible externalities of the Jacobs type. Jacobs (1969) considers that industrial diversity over the same territory leads to a large-scale growth more than specialization. Diversity is a factor that promotes ideas and information exchange, which facilitates rapid internalization of knowledge. A firm located in a given space may benefit from the presence of other neighboring firms operating in different sectors.

2.2.4 Firm size

Glaeser et al. (1992) and Combes (2000) show that firm size is often considered in order to study the impact of local competition on growth. Nevertheless, this index corresponds as well to the average firms' size of a given sector in a geographical area. This leads us to interpret size as a measure of internal economies of scale. Generally, large production units have lower average costs, and then, they will be more performing. This is what constitutes economies of scale internal to the firm. If economies of scale are external to the firm, large production units will less performing (Batisse 2002b).

$$size_{sd} = \frac{nbe_{sd}/VA_{sd}}{nbe_{sl}/VA_{sl}}$$

where nbe_{sd} and nbe_{sl} are, respectively, the number of firms in sector s in delegation d and that of a coastal area l. This index is simply the opposite of the average size of firms in terms of added value.

A positive effect of this variable indicates that the presence of small-size firms in a delegation promotes local growth. Cooperation between these firms may promote local spillovers, which allow them to achieve an optimum production level. By contrast, vertically integrated large production units seem less involved in local networks (Usai and Paci 2003).

2.2.5 Foreign direct investments

The importance of FDIs as a technological spillover-generating mechanism prompted several countries, including Tunisia, to strengthen their attractive benefits and provide financial and tax incentives to foreign investors. Since December 1993,[7] Tunisia has implemented a program to improve FDIs attractiveness conditions by passing the investment incentives code. It turns out that since 1996 the manufacturing sector, for

[6] Ellison and Glaeser (1997) and Batisse (2002a, b) use also the same index to study industrial concentration.

[7] Law no 93–120 of 27th December 1993— Official Government Gazette no 99 of 28/12/1993.

example, has become increasingly attractive. Flows for this sector increased from 49.5 million dinars in 1996 to 374,900,000 dinars in 2005.

Several theoretical and empirical studies, such as Blomström and Persson (1983), Aizenman and Marion (2004) and Bouoiyour and Toufik (2007), have tried to highlight the beneficial effects of FDI while highlighting the impact of the presence of multinational firms on improving productivity and general well-being. New technologies made by these firms will be disseminated afterward by local firms through positive externalities and employment rotation. Furthermore, presence of multinational firms intensifies more competition, which prompts local firms to operate more efficiently. The FDI variable is approximated by the foreign capital participation rate in a particular firm.

2.3 TFP measurement: Olley and Pakes Method (1996)

Several approaches for measuring TFP have been proposed in the empirical literature. In this paper, we use the structural approach developed by Olley and Pakes (1996) in response to simultaneity bias due to the instantaneous correlation between unobservable productivity shocks and inputs. This approach uses the econometric estimation of a production function where the term productivity is an argument of the production function as well as the inputs. Thus, the measure of productivity depends on the quality of estimating production function parameters. Over a panel data and proceeding by a logarithmic transformation of the Cobb Douglass production function, the retained model takes the following form:

$$\begin{aligned} y_{it}^s &= a_0^s + a_k^s k_{it}^s + a_l^s l_{it}^s + u_{it}^s \\ u_{it}^s &= \omega_{it}^s + v_{it}^s \end{aligned} \tag{2}$$

with y_{it}, k_{it} and l_{it} denote, respectively, the output logarithm (or added value), capital and employees; the a_k and a_l coefficients are the to-be-estimated parameters and interpreted as output elasticity relative, respectively, to capital and labor. i and t indicate, respectively, firm and time. The error term u_{it} consists of two segments: a common error term v_{it} specific to econometric models and ω_{it} which represents productivity shocks affecting firm i at time t. This term is observed only by the firm and acts as an input that affects the output as well as capital and employment.

Several types of bias characterize this model. The optimal choice of the production function by the entrepreneur depends on productivity shocks suffered by the firm. The existence of such dependence thus reflects a potential correlation between error term u_{it} and inputs k_{it} and l_{it} which, therefore, are not exogenous. Thus, the violation of some orthogonality conditions makes traditional estimation techniques like OLS provide a non-consistent estimation of the production function parameters. However, the intra or first difference estimator provides consistent estimates of the parameters a_k and a_l, while modeling productivity as a specific fixed effect.

However, the assumption that productivity is invariant in time is too critical, especially if we bear in mind that managers benefit from past experiences of their production process. The technique of instrumental variables provides another alternative, but its implementation in practice suffers from the problem of unavailability of valid instruments. It is indeed very difficult to identify variables that are both correlated with the inputs and orthogonal to productivity shocks ω_{it}. Even past inputs values are generally not valid instruments since the choice of inputs level can be decided through past shocks.

All of these assumptions rally in favor of Olley and Pakes' (1996) structural approach. The authors assumed that labor is a variable factor whose adjustment is instantaneous while capital is assumed to be fixed and whose adjustment is not immediate because of the presence of adjustment costs. At the beginning of each period, the firm chooses the employment level and investment level i_{it}. The authors propose to find *proxies* to productivity shocks. They assume that the shock follows a Markov process and that, in a fixed capital condition, it uniquely determines investment level. Olley and Pakes (1996) use this relationship between productivity and investment to approximate productivity shocks.

In conclusion, the proposed method by Olley and Pakes (1996) provides consistent estimators of the production function parameters and consequently of total factor productivity. The estimation is done in two steps. The first step allows us to estimate output elasticity with respect to labor under the assumption that this factor instantly adjusts productivity shock ω_{it}. The second step is to estimate output elasticity with respect to capital under the assumption that this factor adjusts slowly in response to productivity shocks.

However, the Olley and Pakes approach is based on stringent assumptions that could have implications on the empirical results.[8] First, the model assumes that the relationship between productivity and investment is monotone to ensure the invertibility of the investment demand function. The monotony condition imposed by OP requires the investment to be strictly increasing in productivity. Thus, only observations with positive investment can be used when estimating the model, which can cause a significant loss in the number of observations. Also, if in a significant number of cases firms recorded a zero investment, this casts doubt on the validity of the monotony condition. Second, the model assumes that only the state variable (productivity) is unobservable and is also supposed to evolve according to a first-order Markov process and that there is a one-to-one mapping between the investment and productivity. Or productivity may not be well approximated by a first-order Markov process since productivity could be a complex function of many observable and unobservable factors. More specifically, the investment may depend on other factors that are independent of the productivity, thus violating strict monotonicity condition.

Through a consistent estimation of the production function parameters and a measure of total factor productivity at firm-level PGF_{it}, we adopt the same indicator proposed by Cingano and Schivardi (2004) given by a weighted average TFP at the delegation-sector level:[9]

$$PGF_{sdt} = \frac{1}{N_{sdt}} \times \sum_{i \in (s,d,t)} N_{it} PGF_{it} \tag{3}$$

[8] For more detail, see Ackerberg et al. (2007).

[9] Barbesol and Briant (2008) use a simple average productivity.

where N_{it} and N_{sdt} denotes, respectively, the number of employees of firm i and the total number of employees of sector s in delegation d

3 Data and empirical results

3.1 The statistical data

Our analysis focuses on the Tunisian coastal areas. It consists of eleven governorates (Bizerte, Tunis, Ariana, Ben Arous, Manouba, Zaghouan, Nabeul, Sousse, Monastir, Mahdia and Sfax)[10] with a total of 24 governorates throughout the country. The coastline covers 15 % of total area of the country, but it includes more than 60 % of the global population and 64 % of total employment in 2004. The eleven governorates are administratively organized into 138 delegations corresponding to the spatial scale used for this study. The data used in this paper were taken from the national annual survey report on firms (NASRF) carried out by the Tunisian National Institute of Statistics (TNIS). The data cover nearly all firms for different sectors (initially 5000) and which employ at least ten workers over the period of 1998–2004. Since the data are collected by interviews, the Tunisian NASRF still suffers from a non-response problem. Unfortunately, for the period of 1998–2004, the TNIS does not report any information concerning both the non-response rate of firms and the reasons of non-response.

The initial sample was composed of 1812 manufacturing firms, each one is observed from two to seven years. We conducted the following cleaning of these data using the method attributed to Tukey based on the interquartile range of the variable in question (Kremp 1995). In practical terms, observations situated at more than three interquartile ranges from the first and third quartiles are considered outliers and are then discarded. This cleaning resulted in an unbalanced panel of 7662 observations for 1757 manufacturing firms.

For each firm and sector, we obtained the following data: the number of firms, the number of employees, capital, added value, allocations on research and development, total investment and foreign participation in social capital of the firm. Data are clustered into the following seven major industrial sectors,[11] namely Agri-Food (IAA), textile, clothing and leather (ITHC), rubber and plastic (ICP), chemical industry (ICH), card, paper and edition (IPCE), mechanical engineering, metal, metallurgic and electrical (IMME) and construction materials, ceramics and glass (ICCV) industries.

Tables 4 and 5 in the Appendix report the main descriptive statistics of our sample. We remark the heterogeneity of firms in the sample in terms of size. On average, these firms employ 123 employees and the majority (75 %) employs fewer than 142 employees; it is rather small and medium enterprises in accordance with the Tunisian Industry.

We also know the geographical location of each firm: This information has allowed us to classify firms by spatial unit. Against the work Karray and Driss (2009), in which

[10] see Fig. 1 and Table 3 in the Appendix.

[11] For the sectoral level, the same level was used (digit-2) considered by the APII (Agency for the Promotion of Industry and Innovation) and the CGDR (general commissariat of regional development). Information about digit-3 does not exist.

the authors retain the governorate as the geographical unit of analysis in our study, we use a finer administrative level, namely the delegation. This is the finest geographic unit that can have and provides, in our view, a reasonable number of observations.[12]

3.2 The results

The Cobb–Douglas production function is estimated independently for each sector. Table 6 in Appendix lists the three sets of parameters estimates of the Cobb–Douglas function obtained by different methods, namely ordinary least squares (OLS), fixed effects (FE) and random effects (RE). Table 1 presents the parameter estimates for the production function according to the semi-parametric method of Olley and Pakes (OP). For all these models, all coefficients are highly statistically significant. We report at the bottom of the Table 6 the usual three specific tests to panel data. These are, respectively, tests of absence of fixed effects, random effects and finally the Hausman test of random effects against fixed effects. Results of the first two tests conclude clearly to the rejection of null hypothesis of no fixed effects and random specific effects. The existence of an unobservable heterogeneity is incontestable in our model. The Hausman specification test allows us to choose between FE and RE models. The results of this test conclude that the null hypothesis of orthogonality errors should be rejected. There is thus an instantaneous correlation between the error term, and the production factors, therefore, are not exogenous. The OLS and the MCG estimators are biased and not convergent. However, the fixed effect estimator is unbiased and consistent but suffers from at least two limitations. The first limitation relates to the fact that this estimator does not take into account the variability between firms, and therefore, the estimates will be deprived of their permanent or structural dimension. The second limitation is that this model amounts to accepting the strong hypothesis of invariance of productivity over time. All these remarks militate in favor of the estimates obtained by the semi-parametric method of Olley and Pakes (1996). Under this method, the elasticity of value added with respect to capital and labor is highly significant at the 1 % level. Capital elasticity varies between 0.3 for the ICCV industry and 0.72 for the ICP industry. Labor elasticity varies between 0.468 and 0.755, respectively, for the IAA and ITHC industries. Except for the ICP industry, technological progress is significant and positive.[13] The fourth and fifth row of Table 1 show the scale returns (RE) and the logarithm of total factor productivity.

Once the production function parameters and total factor productivity are estimated, we proceed to regressing TFP on the variables specifying industrial structure. A recurrent criticism of several studies which tried to determine the impact of industrial structure on local growth relates to the failure of taking into account inter-industry heterogeneity. Estimation is made on all industries, assuming that the model applies

[12] In fact, the passage to the governorate scale can result in a considerable decrease in the number of observations. In addition, the use of data across the governorate can hide significant heterogeneity (employment and other variables used in the model) between the various delegations belonging to the same administrative unit (governorate).

[13] Trend is a tendency term introduced in the production function in order to take into account autonomous technical progress.

Table 1 Parameter estimates of production function

	IAA	ICCV	IMME	ICHI	THC	ICP	IPCE
Trend	0.065	0.04	0.028	0.028	0.032	0.009	0.033
	(4.59)	(2.36)	(3.00)	(2.07)	(6.59)	(0.55)	(1.9)
Log(K)	0.549	0.30	0.367	0.311	0.326	0.72	0.352
	(13.15)	(3.28)	(6.04)	(3.56)	(12.64)	(6.63)	(9.67)
Log(L)	0.468	0.69	0.723	0.556	0.755	0.545	0.691
	(6.28)	(12.05)	(27.19)	(11.19)	(61.94)	(10.30)	(17.85)
RE	1.017	0.99	1.09	0.867	1.081	1.265	1.043
Log(TFP)	3.808	3.625	7.14	3.124	5.968	1.301	6.094
R^2	0.829	0.662	0.477	0.89	0.674	0.827	0.658
Num. Obs	789	559	1037	459	3205	319	342

Values in parentheses are the t student of the estimated coefficients; *Num. Obs* indicate the number of observation

identically to all sectors.[14] However, it is more appropriate to assume the presence of an unequal dependence of sectoral TFP on local structures. Thus, the effects and growth prospects may vary from one sector to another. To avoid this, we regress the same basic equation independently for each sector.

The parameter estimates of Eq. (1), as reported in Table 2, show up the presence of an unequal dependence of sectoral TFP on local structures. From these results, we infer that the majority of the coefficients are highly significant and confirm the role of industrial structure in the economic performance of delegations on the Tunisian coast. Bottom of the table are the two specific tests usually conducted on panel data. These are, respectively, the no fixed effect test and the Hausman test of random effects (RE) against fixed effects (FE). The results of the first test clearly reject the null hypothesis of no fixed effects. The presence of an unobservable heterogeneity is undeniable in our model. The Hausman test allows us to choose between the FE and RE models. The result of this test rejects the null hypothesis of errors orthogonality. In what follows, we present the results of the fixed effect model. To correct for a potential heteroscedasticity problem, given the unbalanced nature of data, we transform the model using the Sevestre and Matyas procedure (1992).

For ICCV, IMME, THC and ICP sectors, specialization index has a positive and significant impact on TFP, implying that a specialized industrial environment and geographical grouping of activities belonging to the same sector in a given delegation stimulate growth. Giving that all used variables are in logarithm, the estimated coefficient can be interpreted as elasticity. So, the elasticity of specialization is between 0.072 for the THC industry and 0.23 for the IMME industry. These results are similar to those found out by Glaeser et al. (1992), Cainelli and Leoncini (1999) and Cingano and Schivardi (2004) and support the hypothesis of the presence of dynamic MAR-type externalities, which is generally the case of developing countries. For the IAA and IPCE industries, the effect of specialization is both negative and significant. This

[14] To take into account heterogeneity, some studies include sector-defining variables in the model.

Table 2 Parameter estimates of the basic model

	IAA	ICCV	IMME	ICHI	ITHC	ICP	IPCE
Specialization	−0.085***	0.126***	0.23***	0.086***	0.072***	0.132***	−0.38***
	(−2.26)	(2.59)	(6.34)	(2.03)	(6.78)	(4.43)	(−2.52)
Competition	0.23***	0.084***	−0.077	0.12***	0.124***	0.129**	−0.061
	(5.31)	(2.38)	(−1.11)	(8.27)	(9.28)	(3.41)	(−1.30)
Diversity	−0.009	0.23***	−0.268***	0.011	−0.0016	0.023	0.206**
	(−1.08)	(5.73)	(−2.88)	(1.02)	(−0.62)	1.23)	(2.84)
Firme size	−0.009	0.020	−0.142***	−0.006	−0.079***	−0.066*	−0.137***
	(−1.21)	(1.12)	(−3.95)	(−0.86)	(−19.26)	(−1.95)	(−4.37)
FDI	−0.36***	−0.009	−0.21***	0.238***	−0.07*	−0.037	−0.23***
	(−5.13)	(−0.17)	(−5.52)	(4.33)	(−1.69)	(−1.26)	(−2.47)
R&D	0.008	−0.006	0.281***	0.031***	0.021***	0.058***	−0.032***
	(1.12)	(−0.33)	(7.47)	(3.23)	(8.47)	(4.09)	(−2.45)
Capital	0.24***	0.235***	0.232***	0.193***	0.162***	0.206***	0.211***
	(9.65)	(12.68)	(4.91)	(6.60)	(5.73)	(8.12)	(7.06)
Labor	0.22***	0.208***	0.307***	0.228***	0.359***	0.285***	0.082*
	(9.37)	(12.04)	(4.02)	(14.39)	(8.88)	(11.73)	(1.95)
OLS versus FE test	2.10	3.07	3.46	3.37	1.70	5.70	3.03
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Hausman test	28.49	26.81	20.39	17.54	37.27	33.20	28.11
FE versus RE	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]
R^2	0.72	0.68	0.54	0.77	0.75	0.80	0.73
Num. Obs	359	312	332	187	632	179	177

Values in parentheses are the *t* student of the estimated coefficients; *** indicate significance at 1 %, ** at 5 %, * at 10 %; *Num. Obs* indicates the number of observation for each sector

result indicates the presence of an inverse relationship between regional economic growth and specialization, disproving the MAR model. Excessive specialization can therefore hinder regional development. The more firms are closer to other firms of the same industry, the lower their productivity will be. According to Glaeser et al. (1992) and Combes (2000), a plausible but partial explanation of this negative effect is that industry grows in some areas before it later spreads in space. Note that during the 70s Agrifood industry developed initially in some coastal areas before spreading to other peripheral regions near the coast.

Diversity index is significant only for the ICCV, IMME and IPCE industries. The significantly positive sign of the estimated coefficient (for ICCV and IPCE industries) confirms the importance of intersectoral externalities. Firms benefit from a diverse environment. These urban externalities that are internal to the region are generated thanks to production structures diversity in a particular delegation. We also notice that this positive effect may be specific to the relatively high level of aggregation chosen in this study. The positive impact of diversity may reflect the existing business relationships between sectors and infrastructure availability such as telecommunication and transport rather than the sharing and exploitation of technology across sectors.

According to Batisse (2002a, b), a positive impact of the variable diversity can be articulated as a reflection of existing business relationships between sectors rather than the sharing and exploitation of technological spillovers between sectors. These relationships foster the emergence of virtuous circles that diffuse new and innovative ideas (Cainelli and Leoncini 1999). Moreover, diversity effect is still dominated by the effect of specialization.

Competition index has a significantly positive effect on productivity for the IAA, ICHI, ITHC and ICP industries. It seems that for these industries, market structure (monopoly) contributes less to innovation. In other words, the firm may adapt to its environment by receiving direct or indirect technological externalities. Agglomeration of small-size firms in itself promoted external economies of scale captured under Porter-type local competition. This result contradicts those of Combes (2000), Bun and Makhloufi (2007) and Catin et al. (2007). However, this result is not surprising. According to Porter (1990), a decrease in short-run productivity may be offset by innovation pressure stimulated in the long-run by competition.

Catin et al. (2007) introduced simultaneously the same indicators of competition and average firm size, included in this work, in the regression.[15] Glaeser et al. (1992) consider this variable to be a good proxy of product–market competition. However, this variable corresponds more to the average plant size of sector *s* located in delegation *d* (Batisse 2002a, b). Furthermore, the indicator of local competition used by Glaeser et al. (1992), namely the average firm size, is interpreted rather in terms of dimension effect and can measure from this point of view the potential impact of internal economies of scale (Catin et al. 2007). The significant negative effect of *size* on productivity in the IMME, ITHC and IPCE industries implies that for these sectors, because of an increase in their size, Tunisian firms may achieve productivity gains and internal economies of scale.[16] This result shows that small firms are less productive in size. They fail to create local externalities enabling them to achieve optimal scale of production. By cons, large production units have benefited from lower average costs and internal economies of scale. The presence of many small firms cannot boost technological *spillovers* to promote therefore local growth. This result contradicts on the one hand theoretical expectations and on the other empirical research. It is generally accepted that small firms are more flexible and able to adapt to any structural changes (Combes 2000). This result is not surprising since, in Tunisia, small firms, which constitute the majority of the industrial fabric, are left outside the scope of the upgrading program and vocational training, which are considered means of competitiveness promotion (Bellouti and Castejon 2003).

We found diverse set of results concerning the impact of FDI on productivity. In fact, with the exception of the ICCV and ICP industries, for the other industry, the impact of FDIs is significant, where FDIs are designed to measure the effect of foreign

[15] Cingano and Schivardi (2004) have also introduced simultaneously an indicator of competition and an indicator of size in the regression.

[16] The correlation coefficient between firm size and local competition is but 0.098, which leads us not to interpret firm size as a proxy of local competition. We tried in a first step to estimate the same basic model without the indicator of average firm size and in a second step without the indicator of competition while keeping all other dependent variables in the model. The results do not seem too affected. These results are not reported in the paper but are available under request.

presence in a given sector on firms operating in the same industry. Solely for the ICHI, the spillover effect on productivity is positive and significant where a 10 % increase in foreign firms in a given sector results in an average of 2.38 % increase in productivity. For the IAA, IMME and ITHC industries, this impact become negative. The negative impact of FDIs on productivity is reported by several studies using panel data of developing countries such as Tunisia and Morocco,[17] where conditions necessary for attracting FDIs are not yet met.

Some authors relate this negative effect to a low technological absorption capacity of local firms in these countries. Baccouche et al. (2008) sought to test this hypothesis at firm level. Taking as the unit of analysis Tunisian firms observed over a period stretching from 1998 to 2004, the authors introduce an interaction term linking FDIs and an absorption capacity variable measuring firms' ability to adapt to new standards imposed by foreign firms. They indicate that the spillover effect becomes more and more important when the firm approximates the efficiency curve, and it becomes positive when the firm's adaptability exceeds a certain threshold.

4 Conclusion

Several theoretical and empirical studies have attempted to explain productivity benefits gained by regional industrial and organizational structure. They documented the impact of agglomeration economies on local productivity using employment as a measure. This indirect measure of regional growth, however, gives rise to an identification problem related to an unjustified inference of growth through employment, thereby affecting the robustness of the related results.

In this paper, we align ourselves with the work of Batisse (2002a, b), Catin et al. (2007) and Martin et al. (2011) by using total factor productivity as a direct measure of local economic growth. Using a panel of Tunisian coastal delegations, we have tried to study the impact of agglomeration economies of firms' productivity in view to identify the nature of externalities that contribute most to regional development of different coastal delegations. The analysis of regional disparities in productivity of Tunisian industries is very revealing. To this end, we propose first to compute total factor productivity through estimating Cobb–Douglas production function, using the structural approach of Olley and Pakes (1996) in response to simultaneity bias due to instantaneous correlation between unobservable productivity shocks and production factors. Second, we have regressed TFP on the variables representing industrial structure. The results of the panel- and sector-based estimations indicated the presence of the unequal dependence of sectoral TFP on local structures. Then, growth effects and potential should differ from one sector to another. We find out that industrial productivity in the different delegations might be boosted by their specialization for the ICCV, IMME, ITHC and ICP industries, by a diversified industry for the ICCV and IPCE industries and by competition for the IAA, IICHI, ITHC and ICP industries. The negative effect of FDIs on TFP revealed that local firms could not achieve the expected objectives of creating technological *spillovers*.

[17] The reader can see Baccouche et al. (2008) for the case of Tunisia and Bouoiyour and Toufik (2007) for the case of Morocco.

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Appendix

See Fig. 1 and Tables 3, 4, 5, 6, 7.

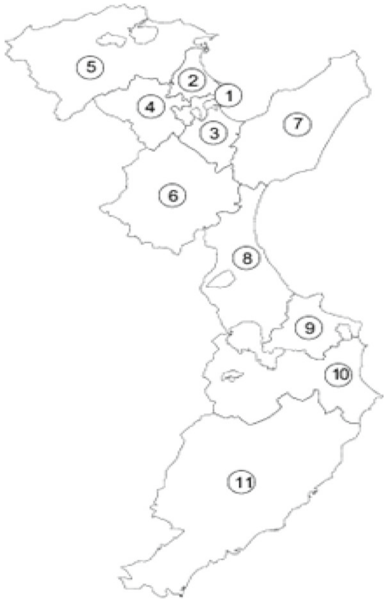

Fig. 1 The eleven coastal governorates: *1* Tunis, *2* Ariana, *3* Ben Arous, *4* Manouba, *5* Bizerte, *6* Zaghouan, *7* Nabeul, *8* Sousse, *9* Monastir, *10* Mahdia et *11* Sfax

Table 3 Number of delegation by governorate

Governorates	Tunis	Ariana	Ben Arous	Manouba	Bizerte	Zaghouan	Nabeul	Sousse	Monastir	Mahdia	Sfax
Number of delegation	21	7	12	8	14	6	16	15	13	10	16

Table 4 Average annual growth between 1998–2004

Governorates	Number of employees	Value added	Number of firms
Tunis	−4.24	2.03	−4.43
Ben Arouss	−6.43	−1.65	−8.66
Arianna	1.79	5.13	−0.14
Nabeul	8.31	13.66	3.35
Zaghouan	34.52	25.21	11.68
Bizerte	1.42	6.86	−5.06
Sousse	1.73	2.37	0.37
Monastir	8.73	15.15	2.39
Mehdia	10.86	24.66	7.57
Sfax	−0.41	5.46	−4.90

Table 5 Descriptive statistics

Variable	IAA		ICCV		IMEE		ICHI		ITHC		ICP		IPCE	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Value added	2,633,082	5,549,860	2,179,328	5,180,629	1,725,365	3,083,883	5,656,535	27,054,867	970,269	2,183,736	1,509,405	4,460,635	1,563,973	2,756,240
Capital	9,133,523	16,025,463	10,465,284	27,015,247	4,322,235	10,729,186	17,968,347	99,017,234	1,458,492	5,984,623	4,762,825	1,471,253	4,661,393	9,146,337
Num. employees	101	186.18	104	144.77	114	164.25	150	528.46	135	159.75	81	137.43	73	99.48
Specialization	2.040	2.254	2.464	3.265	6.946	12.122	1.140	1.192	1.869	1.235	3.413	4.68	4.021	6.614
Competition	12.654	23.194	49.772	65.394	7.456	12.478	12.860	26.425	3.745	22.887	4.976	13.261	8.017	20.67
Diversity	5.704	25.322	1.399	7.404	1.022	4.043	0.854	1.480	12.310	53.726	3.737	39.210	2.654	14.648
Firm size	0.795	0.368	0.841	0.342	0.861	0.332	0.763	0.409	0.775	0.40	0.852	0.321	0.868	0.323
FDI	0.092	0.256	0.167	0.338	0.328	0.427	0.210	0.367	0.485	0.363	0.252	0.402	0.050	0.196

Table 6 Parameter estimates of production function

	IAA			IMCCV			IMME			ICHI		
	OLS	FE	RE	OLS	FE	RE	OLS	FE	RE	OLS	FE	RE
Const.	3.16	3.207	3.176	4.172	3.886	4.204	4.886	6.192	5.479	4.773	3.619	4.322
	(10.60)	(6.99)	(9.39)	(9.90)	(6.66)	(8.91)	(7.21)	(6.51)	(7.67)	(10.74)	(5.70)	(8.65)
Log(K)	0.579	0.596	0.584	0.441	0.491	0.436	0.428	0.33	0.365	0.44	0.618	0.514
	(19.34)	(14.03)	(17.58)	(9.33)	(8.17)	(8.65)	(6.93)	(3.53)	(5.46)	(9.70)	(9.70)	(10.12)
Log(L)	0.47	0.406	0.451	0.621	0.597	0.614	0.618	0.621	0.679	0.628	0.315	0.479
	(10.58)	(6.91)	(9.22)	(7.77)	(5.28)	(7.30)	(7.71)	(4.01)	(7.19)	(9.87)	(3.59)	(6.58)
Trend	0.041	0.033	0.028	0.037	0.033	0.038	0.018	0.022	0.024	0.020	0.172	0.024
	(3.45)	(2.57)	(2.36)	(3.43)	(2.77)	(2.07)	(2.13)	(2.26)	(3.14)	(1.87)	(0.73)	(3.12)
OLS versus FE test	–	3.91	–		6.08			5.76			10.41	
	–	(0.000)	–		(0.000)			(0.000)			(0.000)	
Breusch–Pagan test	–	–	14.12			9.85			30.41			18.13
OLS versus RE	–	–	(0.000)			(0.001)			(0.000)			(0.000)
Hausman test:	–	–	45.19			49.35			69.27			41.59
	-		(0.000)									
FE versus RE	–	–	45.19			(0.000)			(0.000)			(0.004)
			(0.000)									
R^2	0.81	0.79	0.81	0.77	0.71	0.82	0.65	0.58	0.64	0.89	0.75	0.86
Number of observations	1010	1010	1010	683	683	683	1194	1194	1194	498	498	498

Table 6 continued

	ITHC			ICP			ICPEI		
	OLS	FE	RE	OLS	FE	RE	OLS	FE	RE
Const.	5.319	5.792	5.74	4.281	4.363	4.132	4.33	4.468	4.244
	(22.26)	(16.11)	(19.29)	(4.90)	(4.52)	(5.23)	(6.93)	(4.22)	(5.71)
Log(K)	0.303	0.284	0.279	0.678	0.672	0.696	0.372	0.465	0.408
	(12.76)	(8.43)	(9.67)	(12.34)	(8.18)	(10.62)	(9.94)	(4.89)	(5.57)
Log(L)	0.778	0.73	0.767	0.328	0.358	0.335	0.875	0.51	0.765
	(28.21)	(18.44)	(22.37)	(4.82)	(3.93)	(4.34)	(10.10)	(3.32)	(7.13)
Trend	0.035	0.035	0.033	0.004	0.010	0.009	0.037	0.04	0.033
	(3.44)	(4.07)	(4.06)	(0.61)	(1.32)	(1.14)	(1.52)	(1.69)	(1.78)
OLS versus FE test		4.59			4.16			4.83	
		(0.000)			(0.000)			(0.000)	
Breusch–Pagan test			69.27			35.12			17.18
OLS versus RE			(0.000)			(0.000)			(0.000)
Hausman test:			88.73			52.90			40.22
FE versus RE			(0.000)			(0.000)			(0.000)
R^2	0.78	0.60	0.80	0.91	0.70	0.89	0.77	0.69	0.74
Number of observations	3517	3517	3517	383	383	383	377	377	377

Table 7 Average annual growth of TFP per sector and governorate

Governorate	IAA	ICCV	IMME	ICHI	ITHC	ICP	IPCE
Tunis	−1.25	38.32	0.25	0.986	4.3	8.25	6.72
Ariana	4.05	39.32	13.06	−5.26	0.3	−3.6	18.04
Ben Arous	1.48	5.05	−1.55	0.406	3.83	3.85	7.23
Manouba	4.87	3.49	−7.08	−4.877	2.84	−4.7	−18.2
Bizerte	3.47	11.06	3.42	161.29	3.68	−8.94	13.68
Zaghouan	–	10.56	–	–	6.06	−1.507	–
Nabeul	3.22	−6.168	−15.38	0.754	3.036	–	−0.16
Sousse	−1.48	4.96	−0.697	−0.625	3.1	−0.1	11.62
Monastir	2.125	3.9	−3.61	20.62	5.26	30.79	28.3
Mahdia	6.99	−2.48	–	22.13	0.834	–	–
Sfax	2.3	5.94	3.97	−1.289	2.79	−2.1	10.28

Correlation matrix

	Log(sp)	Log(comp)	Log(div)	Log(size)	FDI	Log(RD)	Log(K)	Log(L)
Log(sp)	1.000							
Log(comp)	−0.369	1.000						
Log(div)	−0.297	−0.016	1.000					
Log(size)	−0.074	−0.098	−0.088	1.000				
FDI	0.241	−0.368	0.000	0.228	1.000			
Log(RD)	0.215	−0.208	0.000	−0.166	0.074	1.000		
Log(K)	0.236	−0.480	0.123	−0.273	0.039	0.405	1.000	
Log(L)	0.439	−0.394	0.096	−0.308	0.151	0.392	0.745	1.000

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