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ORIGINAL PAPER

Firm and regional factors of productivity: a multilevel analysis of Tunisian manufacturing

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Abstract
In this paper, we use multilevel models to simultaneously analyze individual, sectoral and regional characteristics that might affect the total factor productivity of Tunisian manufacturing firms for the period 1998–2004. Our results show that the individual characteristics of the firm have an important effect on both total factor productivity and labor productivity. We find that the oldest small firms are more productive than larger firms. Regional context has a significant direct impact on firms' performance. More specifically, industrial density has a positive influence on total factor productivity. Our results show also that interaction effects or indirect effects are mostly driven by sectoral characteristics. The intra-industrial wage disparities are beneficial only for firms with higher human capital and R&D. The interaction effects also show that larger and older firms will benefit more from industrial agglomeration. We conclude that multilevel models better fit our research questions that combine firm and contextual characteristics simultaneously, because they allow firm-specific characteristics to be differently associated to their regional and sectoral contexts.

JEL Classification D22 · L11 · L25 · R12

1 Introduction

There is a wide consensus on the necessity of understanding productivity growth in order to reduce the efficiency gap and to ensure the convergence of productivity among industries and regions. This interest was largely motivated by recent empirical

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literature on economic growth showing that regional disparities in the productivity levels represent one of the key determinants of the income differences and inequality (Dettori et al. 2012; Easterly and Levine 2001; Caselli 2005; Rice et al. 2006, among others). The lion's share of productivity research has tended to take either a regional-level (macro-level) approach, focusing on the characteristics of ecological units such as cities and countries, or a firm-level (micro-level) focusing on the characteristics of the firm. At the regional level, several explanations of the productivity gap have been put forward, but the key role appears to be related to intrinsic differences among regions such as infrastructure, human capital, and levels of research and development (Krugman 1991; Romer 1990; Lucas 1988; Moretti 2004; Ciccone and Peri 2006; Bronzini and Piselli 2009; Andersson and Lööf 2011; Glaeser et al. 2002).

At the firm level, scholars argue that firm-specific characteristics (age, size, type of economic activity, human capital and internal R&D), and industrial structure or external variables (knowledge spillovers, specialization, diversity, competition) explain firms' performance (Audretsch and Feldman 2004; Henderson 2007). Some recent studies propose an alternative approach that allows micro-levels and macro-levels to be modeled simultaneously in order to explain the differences in the total factor productivity (henceforth TFP): It is the so-called the multilevel or the hierarchical model (e.g. Aiello et al. 2014; Fazio and Piacentino 2010; Raspe and Van Oort 2011).

By using multilevel modeling, it is possible to explain the differences in the TFP by providing a clear distinction between firm and region-specific effects. In addition, it is possible to show how contextual effects translate into individual behavior. Fazio and Piacentino (2010) argue that multilevel modeling can also reduce the ambiguity surrounding the agglomeration-firm performance relationship and address regional, sectoral and cross-level heterogeneity. Raspe and Van Oort (2011) believe that "existing single-level methodologies can be problematic and that alternative methodologies (such as multilevel analysis) provide a useful empirical framework to address potential ecological measurement fallacies". If micro- and macro-factors affect productivity and interact with each other, their contribution can be properly measured only via a multilevel analysis that can solve the micro–macro-problem known as "ecological fallacy" (Robinson 1950) or "cross-level fallacy" (Alker 1969). If one of the relevant dimensions (individual or regional) is omitted, estimations of the determinants of TFP are bound to be biased.

In this paper, we use an unbalanced panel of more than 2843 Tunisian manufacturing firms over the period 1998–2004 to estimate how much of the observed firm-level performance due to firm-specific characteristics. In addition, we test how regional and sectoral characteristics affect the productivity of firms. In this respect, Tunisia provides a very relevant context to examine these issues. Indeed, Tunisian economic activities are characterized by large inter-regional and inter-sectoral productivity gaps. Nearly 56% of the total population and 92% of all industrial firms are concentrated in the three largest cities: Tunis, Sfax and Sousse. These three coastal towns, which form the core of economic activity, represent 85% of the national GDP. Moreover, large productivity gaps exist across sectors (Marouani and Mouelhi 2016). By considering the interaction of micro-data at the firm level and macro-data at the regional and sectoral levels, we are able to control the individual, regional and sectoral heterogeneity for the evaluation of firm-level productivity. We can also overcome the endogeneity and multicollinearity problems so critical in empirical studies that rely on aggregate data only to investigate the relevance of the socioeconomic context for economic activity (Fazio and Piacentino 2010). Moreover, the multilevel analysis allows the inclusion of macro-level (regional and/or sectoral) exploratory variables which otherwise would be absorbed by the fixed effects. In addition, the multilevel analysis, by using a single equation model, exploits the structures of data and properly addresses the issue of error correlation across firms that operate in the same region and in the same sector.

Most previous studies in Tunisia tend to analyze productivity either at the firm level or at the regional level. For example, Baccouche et al. (2008) use a firm-level data to examine the relationship between foreign direct investment (FDI) and total factor productivity (TFP) in Tunisian manufacturing sectors during the period 1998–2004. Amara and Thabet (2012) and Thabet (2015) test the impacts of the local industrial structure (specialization, diversity, competitiveness and the firm's size) on the aggregated added value for five industrial sectors among 138 delegations of the coastal areas of Tunisia over the period 1998–2004. Amara and El Lahga (2015) have recently used a sample of manufacturing Tunisian firms to distinguish between the effects of own firm's characteristics (direct effects) and average characteristics of their neighbors (endogenous and contextual effects) on its output level. Marouani and Mouelhi (2016) separately use sectoral and firm data to analyze the dynamics of sectoral productivity growth in Tunisia and assess the contribution of structural change to these dynamics. To the best of our knowledge, our study is among the first in Tunisia to consider micro- and macro-interaction to examine the productivity of manufacturing firms.[1]

The remaining of the paper is organized as follows. We briefly conduct a comprehensive literature review in the field of predicting and understanding the determinants of TFP as well as a short description of the economic geography of Tunisia in Sect. 2. We then present the data and the methodology employed to estimate the contribution of each micro-level and macro-level factor on the firm-level TFP (Sect. 3) and an overview of the main results in Sect. 4. Section 5 concludes with some policy recommendations.

2 Firm productivity and regional disparity in Tunisia: brief review

In the literature reviews, productivity is considered at two different levels: the micro-level and the macro-level. In micro-level, and given the increasing availability of individual firm data, a growing number of studies have tried to identify what factors influence the productivity of firms. Most of these studies have been carried in advanced economies, such as the USA, Germany, France, Italy and the UK (Keller and Yeaple 2009; Wagner 2007; Martin et al. 2011; Parisi et al. 2006; Wakelin 2001). Firms are naturally influenced by their own attributes and resources (also known as internal factors) such as competencies, knowledge and human capital (Backman 2014). Human capital can impact the firm's performance through several

[1] The key work in this field is that of Van Oort et al. (2012). See also Smit et al. (2015) for an interesting investigation in how micro and macro levels affect the propensity of firms to innovate.

mechanisms (Ballot et al. 2001): (1) a firm which has substantial human capital will make better decisions than its rivals with lower human capital; (2) innovation will be stimulated by the quality and training of the personnel in the R&D department; (3) learning-by-doing is also higher if workers have high human capital. Using data from two panels of large French and Swedish firms for the same period 1987–1993, Ballot et al. (2001) show that firm-sponsored training and R&D are significant inputs in the two countries.

The empirical literature also suggests that firm size and firm age have a positive impact on productivity. Indeed, firm size largely determines a firm's resource base, competencies and scale advantages. Due to internal economies of scale that reduce the per-unit costs over the number of units produced, efficiency advantages emerge from larger firm sizes, while small firms have to overcome these disadvantages (Jovanovic 1982; Raspe and Van Oort; 2011). In addition to size, a number of studies bring to the fore that learning process and firm experience (Majumdar 1997; Raspe and Van Oort 2011) and spin-offs (John and Ofek 1995; Berger and Ofek 1999; Chemmanur et al. 2014) are important for firm-level productivity.

In addition to internal factors and firms' resources, the external factors are important for firm performance. Still remaining at micro-level, the concept of knowledge spillovers and firm productivity has received increasing interest over the past decades (Henderson et al. 1995; Audretsch and Feldman 1996; Ellison and Glaeser 1997; Rice et al. 2006). Recently theoretical developments have attempted to open the 'black box' of knowledge spillovers and to explain how these spillovers work at the micro-level (Duranton and Puga 2004; Henderson 2007). In other words, they seek to understand how local interactions, peer effects, spatial relationships, labor mobility, and social networks lead to better firm performance, such as productivity levels (Ciccone and Hall 1996; Cingano and Schivardi 2004; Stoyanov and Zubanov 2012) and innovation (Smit et al. 2015).

Taking the analysis to the regional-level, productivity gaps and regional convergence are issues of intense theoretical and empirical research since the development of New Growth theory and New Economic Geography (Rice et al. 2006; Ke 2010; Bronzini and Piselli 2009). These studies suggest that regional gap in productivity can be attributed to regional differences in various factors such as education endowment, foreign direct investment (FDI), producer's market accessibility, customer's market accessibility, and agglomeration economies. These factors contribute to the agglomeration of firms in urban areas. Indeed, Krugman (1991) showed that decline in transport costs, increases of economies of scale, and mobility of the specialized labor reinforce agglomeration of firms and increase regional disparities. The World Bank Annual Report (2009): *Reshaping Economic Geography* states also that "*Markets favor some places over others, some places-cities, coastal area, and connected countries are favored by producers*".

Tunisia's economic growth also fits this pattern. Although the Tunisian economy has shown robust economic growth over the past decade (the aggregate growth was about 5 percent per year since the late 1990s), wide-spread inequalities between coastal and inner regions persist. Private sector activity is heavily concentrated along the coast. In particular, almost all industrial firms are located close to the three coastal agglomerations of greater Tunis, Sfax, and Sousse. More than 90% of total employment is still generated in the coastal part of the country. Similarly, unemployment rates show considerable disparities across regions and are especially high in the interior regions. The interior areas have the highest unemployment rate (18.5%) as opposed to 13.1% in the coastal area (Amara and Ayadi 2014). The unemployment rate is higher for women (19% in 2010) than for average (11%), and twice as high for graduate women (33%) as for graduate mean (16%). Moreover, the investment incentives code, by favoring export-oriented production, has heavily favored investment in coastal areas, and may, therefore, have played a role in deepening regional disparities.

In addition, the social situation in Tunisia has dramatically worsened in recent years due to the rise of the informal sector, the pandemic growth of corruption, and the failure or the inability of the formal sector to guarantee the desired level of employment.

3 Data sources and methodology

3.1 Data

Data used in this paper are drawn from the National Annual Survey Reports on Firms (NASRF) conducted by the National Institute of Statistics (INS).[2] The dataset refers to an unbalanced panel of about 2843 firms between 1998 and 2004 from the agro-food (IAA), the textiles, wearing, leather and footwear (ITHC), the construction materials, ceramic and glass (IMCCV), the mechanic, electric and electronic (IME), the chemical (ICH) and the other manufacturing industries (ID). The firm's activity is described by a one-digit Tunisian nomenclature of economic activities. The dataset was cleaned from outlier observations. More specifically, we exclude firms with fewer than six employees as well as these with negative added value or zero investment. The dataset includes added value, investment, firm's birth date, capital stock, foreign capital participation, expenditure in information and communication technology, expenditure in R&D, exporting rate and labor (number of employees). The number of employees involves the number of engineers and managers used to approximate human capital.

Table 1 presents the annual average distribution of firm size and employment. Over the period 1998–2004, firms with 20–49 employees account for approximately 25% of all firms, and 7% of employment. On average, in each year there are only 13 firms that employed at least a thousand workers which represents no more than 1% of all firms. However, these firms account for 13.72% of all employment and are also the oldest with an average age of 25 years.

[2] The INS collects annual unbalanced-sheet data on a sample of 5000 firms covering almost all formal sectors (the firm that has employed six or more people), out of which 2000 responded to the questionnaire. In parallel with the NASRF' survey, covering almost all formal sector firms, a survey of small firms (with fewer than six employees) has been conducted by the INS every 5 years since 1997. The national register of establishments that is continuously updated provides a safe basis for the sampling of both surveys.

Table 1 Firm size and employment distributions (annual averages 1998–2004)

Size category # of workers	# of Firms	% of Firms	# of Jobs	% of Employment	Age (years)
[6, 9]	68	05.05	514	0.33	17.39
[10, 19]	171	12.79	2422	1.53	18.09
[20, 49]	331	24.75	10,834	6.86	18.40
[50, 99]	294	21.95	20,892	13.22	17.15
[100, 199]	280	20.95	39,175	24.79	19.09
[200, 999]	182	13.58	62,503	39.56	20.98
≥ 1000	13	00.94	21,672	13.72	25.22
Total	1338		158,012		18.67

Table 2 Firm and employment distributions by sector (annual averages 1998–2004)

Sector	# of Firms	% of Firms	# of Jobs	% of Employment
IAA	166	12.37	14,169	8.97
ITHC	654	48.86	86,178	54.54
IMCCV	105	07.84	10,813	6.84
IME	228	17.04	28,288	17.90
ICH	70	05.24	9700	6.14
ID	116	08.66	8883	5.61
Total	1338		158,012	

Table 3 Firm and employment distributions by region (annual averages 1998–2004)

Region	# of Firms	% of Firms	# of Jobs	% of Employment
Greater Tunis	355	26.54	47,468	30.04
North-East	247	18.47	35,101	22.21
North-West	17	01.27	2633	01.67
Center-East	663	49.56	68,067	43.08
Center-West	15	01.14	2089	01.32
South-East	38	02.86	2598	01.64
South-West	2	00.16	56	00.04
Total	1338		158,012	

Table 2 shows the annual average of the number of firms as well as their employment by sector for the full sample of data. The distribution shows a concentration of firms in ITHC (49%) and in IME sectors (17%). Moreover, Table 2 indicates that more than half (55%) of employment is generated by the ITHC sector and 18% by the IME sector. Table 3 presents the annual average distribution of firms and manufacturing jobs by region. Firms and employment are largely concentrated in a small number of cities. The three coastal regions (Greater Tunis, North-East and the

Center-East) account for around 95% of total firms and 95% of manufacturing jobs, and Center-East alone for 49.56% of total manufacturing firms. While, on average, the total number of manufacturing firms in the Center-West region does not exceed 15 firms (1.14% of all firms).

3.2 Variable definitions

3.2.1 Firm-level variables

In this paper, the dependent variable is defined as the firm's TFP. As a good robustness check, we use the labor productivity (measured as value added per employee) as the second dependent variable.[3] 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. Over a panel data and proceeding by a logarithmic transformation of the Cobb Douglass production function, the estimating equation is giving by:

$$\begin{aligned} y_{it} &= a_0 + a_k k_{it} + a_l l_{it} + u_{it} \\ u_{it} &= \omega_{it} + \eta_{it} \end{aligned} \tag{1}$$

where y_{it} is the log of output (value added) from firm i at time t, k_{it} the log of its capital and l_{it} the log of its labor input; the a_k and a_l coefficients are the to-be-estimated parameters (interpreted also as output elasticity relative, respectively, to capital and labor). The error term u_{it} consists of two components: the stochastic term η_{it} and the productivity ω_{it}. η_{it} is a zero expected mean that uncorrelated with the input choices and unknown to firm and researcher. ω_{it} is known to the firm but unknown to the researcher and acts as a state variable to which a firm adjusts its input choices (capital and labor).

Several types of bias emerge when TFP is estimated using the Ordinary Least Squares (OLS) estimator. First, the optimal firm's choice of input quantities will be determined by prior beliefs about its productivity level. Hence, the productivity level and input choices are likely to be correlated. The existence of such dependence reflects a potential correlation between error term u_{it} and inputs (k_{it} and l_{it}) which, therefore, are not exogenous. This problem, known as simultaneity bias, violates the orthogonality conditions that make OLS provides a non-consistent estimation of the production function parameters.[4] Second, if no allowance is made for firm entry and exit, selection bias will emerge. In this paper, we don't deal with the selection bias

[3] See Del Gatto et al. (2011) for more details on measuring productivity.

[4] The 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.

by using firm-level data because we do not have accurate information on entry and exit decisions.[5] We only consider the simultaneity bias, and we chose to apply the structural approach proposed in Olley and Pakes (1996) to solve this problem.[6] In addition, we exploit the availability of aggregated data on entry-exit patterns at sectoral and regional levels to minimize the selection bias.

Olley and Pakes (1996) suppose that at each time period t, the firm aims to maximize the expected value of its current and future profits and must decide its investment level to survive. If there is no exit (firm continuous in operation), investment is a function of current state variables.

$$i_{it} = f_t\left(\omega_{it}, k_{it}\right) \tag{2}$$

Olley and Pakes (1996) show that investment (if it is nonzero) is strictly increasing in productivity giving k_{it}, so we have:

$$\omega_{it} = f_t^{-1}\left(i_{it}, k_{it}\right) = h_t\left(i_{it}, k_{it}\right) \tag{3}$$

Equation (3) expresses productivity as a function of capital and investment which are both observables. This fact allows us to correct the simultaneity problem as follows:

$$\begin{aligned} y_{it} &= a_0 + a_k k_{it} + a_l l_{it} + h_t\left(i_{it}, k_{it}\right) + \eta_{it} \\ &= a_l l_{it} + \phi\left(i_{it}, k_{it}\right) + \eta_{it} \end{aligned} \tag{4}$$

where $\phi\left(i_{it}, k_{it}\right) = a_0 + a_k k_{it} + h_t\left(i_{it}, k_{it}\right)$ is approximated by a higher-order polynomial in i_{it} and k_{it}. This step provides a consistent estimate of the labor elasticity.

To estimate the coefficient on the capital variable, it is necessary to exploit information on firm dynamics. To do this, Olley and Pakes (1996) assume that productivity follows a first-order Markov process as:

$$\begin{aligned} \omega_{it} &= E\left[\omega_{it} | \omega_{i,t-1}\right] + \xi_{it} \\ &= g\left(\omega_{i,t-1}\right) + \xi_{it} \end{aligned} \tag{5}$$

where ξ_{it} is an innovation with zero mean uncorrelated with k_{it} ($E\left(\xi_{it} | k_{it}\right) = 0$). The function $g(.)$ is unknown and it is always possible to be approximated by a polynomial function. This second step consists firstly to eliminate the contribution of labor to output which was estimated in the first step to obtain the following model (see Petrin et al. 2004 for more details):

[5] Note that the selection bias emerges once the selection process is not random. Or we have not exact information about the reason for exit in our data. In fact, our data are drawn from the National Annual Survey Reports on Firms (NASRF) conducted by the National Institute of Statistics (INS) where the exit can reflect, simply, a non-response problem.

[6] There are many other approaches that solve the endogeneity problem like those proposed by Levinsohn and Petrin (2003) and Ackerberg et al. (2007) but we don't use them because we don't dispose information about the intermediate input which constitutes a basic variable for these methods.

$$
\begin{aligned}
y_{it} - a_l l_{it} &= a_0 + a_k k_{it} + \omega_{it} + \eta_{it} \\
&= a_k k_{it} + E\left[\omega_{it} | \omega_{i,t-1}\right] + \xi_{it} + \eta_{it} \\
&= a_k k_{it} + g\left(\omega_{i,t-1}\right) + \xi_{it} + \eta_{it} \\
&= a_k k_{it} + g\left(\hat{\phi}_{i,t-1} - a_0 - a_k k_{i,t-1}\right) + \xi_{it} + \eta_{it}
\end{aligned} \tag{6}
$$

Once the production function parameters have been estimated, one can infer the total factor productivity using the following formula:[7]

$$
tfp_{it} = \log\left(\mathrm{TFP}_{it}\right) = \omega_{it} = h_{it}(.) \tag{7}
$$

The choice of the independent variables at the firm-level is based on the empirical and theoretical studies presented in section II. Most specifically, we expect TFP to rise with R&D intensity ($R\&D_{ij}$) (Hall and Mairesse 1995). Human capital (H_{ij}), foreign direct investment (FDI_{ij})[8] and capital intensity ($\mathrm{capital}_{ij}$) were also tested as determinants of TFP. Human capital (the number of engineers and managers divided by the total number of employees) is expected to correlate positively with firms' performance (Black and Lynch 1996, Girma 2005). In addition, we believe that the size of the firm (size_{ij}), the size square (sizesq_{ij}) its age (age_{ij}), the age square (agesq_{ij}) and the type of economic activity (sector_{ij}) have an impact on TFP (Raspe and van Oort 2011).

3.2.2 Regional variables

To evaluate the agglomeration economies, we include two measures: the specialization index (SPEC_j) that captures the degree of industrial specialization (MAR externalities) and the inverse of Hirschman–Herfindahl index (DIV_j), which is the most common measure to account for Jacobs externalities (Beaudry and Schiffauerova 2009, Combes 2000). We use the Krugman specialization index as a relative measure of regional specialization, where the formula is the following:

$$
\mathrm{SPEC}_j = \sum_s \left| \frac{\mathrm{emp}_{js}}{\mathrm{emp}_j} - \frac{\mathrm{emp}_j}{\mathrm{emp}} \right| \tag{8}
$$

where emp_j and emp are the total employment and emp_{js} and emp_s are the sectoral employment in governorate j and Tunisia, respectively. The index takes values in the interval [0, 2], where 0 indicates governorates with completely identical structure and 2 indicates governorates with a completely different industrial structure between the regional and the reference economy.

[7] We use the levpet Stata routine provided by Levinsohn and Petrin (2003) to estimate TFP. We are unable to use the opreg command developed by Yasar et al. (2008) because we lack the data on the entry and exit rates (this information is required to estimate the TFP by opreg Stata routine). The parameter estimates of the production functions and the annual averages TFP and LP for each sector are presented, respectively, in Tables 8 and 9 of the "Appendix".

[8] The FDI is a dummy variable that takes 1 if the foreign capital participation is more than 10% and 0 otherwise.

For each governorate j the Hirschman-Herfindahl index sums over all industries the square of the share of governorate j's employment relative to total (national) employment in industry s:

$$\mathrm{DIV}_j = 1/\left(\sum_s \left(\frac{\mathrm{emp}_{js}}{\mathrm{emp}_j}\right)^2\right) \tag{9}$$

$\mathrm{DIV}_j = 1$ if economic activity in the governorate under consideration is fully concentrated in one industry and increases as activities in the city become more diverse.

Information on wage differences across areas is also fundamental to explain total factor productivity (Krugman 1991). The New Economic Geography (NEG) identifies wage differences as one of the major determinants of firms' location decisions and the emergence of a core-periphery structure. Combes et al. (2008) proposed three broad arguments to explain the origin of spatial wage disparities. First, spatial differences in the skill composition of the workforce directly affect wage disparities. Second, wage differences across areas are caused by differences in local nonhuman endowments (geographical features, natural resources, or some other local endowments like public or private capital, local institutions, and technology). The third interpretation considers that some interactions between workers or firms lead to productivity gains. In our analysis, we use the Gini coefficient ($\mathrm{Gini\_wage}_j$) to measure the regional wage disparities across governorates.

We also suppose that the presence of foreign direct investment within a region is an important factor of firms' TFP. It has been argued that foreign investment is likely to be associated with the transfer of knowledge and spillovers, such as management skills and quality systems (Javorcik 2004). We use the share of FDI firms in the governorate (FDI_j) to measure the presence of the FDI.

There is some evidence that the turnover of firms is higher in some regions than others. A high rate of firm turnover can positively affect regional productivity growth if it reflects a transfer of resources from less efficient (exiting firms) to more efficient producers (survivors). In order to test this idea, we use the regional volatility rate ($\mathrm{volatility}_j$) defined as:[9]

$$\mathrm{volatility}_j = \left(\mathrm{entry\ \ rate}_j + \mathrm{exit\ rate}_j\right) - \left|\mathrm{entry\ \ rate}_j - \mathrm{exit\ rate}_j\right| \tag{10}$$

It is the sum of the entry and exit rate minus the absolute value of the net entry rate at the governorate level.[10]

[9] The volatility rate is widely used to test how firm turnover can contribute to industry productivity growth (Aw et al. 2000; Aw et al. 2001). We extend this measure to test the firm's turnover effect at the regional level.

[10] The firm entry rate will be calculated as the number of entrants (all manufacturing industries) during a certain period (the year), divided by the total number of firms (all manufacturing industries) in the governorate. The firm exit rate will be calculated as the number of exiting firms divided by the total number of firms in the governorate. We use the aggregate (at sectoral and regional level) data from the Tunisian Business Register (*Répertoire National des Entreprises*) to calculate firm entry and exit rates.

In addition to regional volatility rate, we control for regional education level, measured as the number of highly educated (university) employees in the total regional employment and the market size (population density and the number of industrial employees per 1000 inhabitants). Finally, the unemployment rate by governorate is included.

3.2.3 Industrial structure or industry-level variables

As discussed earlier, industrial agglomeration is helpful in generating information spillovers within the region. Following most existing studies, we use the agglomeration index developed by Ellison and Glaeser (1997), also known as the EG index, to examine the degree of industrial agglomeration. Compared to other agglomeration indices, such as the Gini index and Hoover's coefficient of localization, the EG index purges the own firm size from industrial concentration. The EG index, can, therefore, distinguish between concentration arising from the industrial structure from concentration arising from agglomeration externalities (Rosenthal and Strange 2001). Indeed, industrial concentration can be simply due to the existence of a small number of large plants and that there is no agglomeration force. To address this problem, Ellison and Glaeser propose the following agglomeration index to measure the degree of each industry's agglomeration:

$$\gamma_s = \mathrm{EG}-\mathrm{index}_s = \frac{G_s - \left(1 - \sum_j X_j^2\right) H_s}{\left(1 - \sum_j X_j^2\right)\left(1 - H_s\right)},\ G_s = \sum_j \left(S_{sj} - X_j\right)^2,\ H_s = \sum_i z_{is}^2 \tag{11}$$

where G_s represents the raw geographical concentration, S_{sj} denotes the employment share of industry s in governorate j and X_j is the share of aggregate manufacturing employment (all industries) in the governorate. H_s is the Herfindahl–Hirschman index measured as the sum of squares of firm i's employment to industry share (z_{is}). In addition to the industrial agglomeration variable, we also test the impact of the intra-industry wage differentials and the industrial volatility on TFP.

$$\mathrm{volatility}_s = \left(\mathrm{entry\ rate}_s + \mathrm{exit\ \ rate}_s\right) - \left|\mathrm{entry\ \ rate}_s - \mathrm{exit\ \ rate}_s\right|. \tag{12}$$

Table 4 gives descriptive statistics for dependent and independent variables.

3.3 Methodology

In this study, we have used multilevel modeling that exploits the hierarchical structure of the data in order to determine the direct effect of the individual (firm) and group (governorate or sector) explanatory variables, as well as the interactions between them (Snijders and Bosker 1999). Thus, we can assess the extent to which variance in firms' TFP can be attributed to between-firm variance, between-governorate variance, or between-industry variance (Van Oort et al. 2012). Considering an empty model that decomposes the variance of firm's productivity Y_{ij} (measured by the log of total factor productivity of firm i nested at governorate j) into two independent components: σ_e^2, the variance of the lowest level (firm level) errors e_{ij}, and $\sigma_{u_0}^2$, the variance of the highest level (regional or industrial level) errors μ_{0j}. The empty model, named also as the random intercept-only model or null model, is modeled as:

$$Y_{ij} = \gamma_{00} + \mu_{0j} + e_{ij} \tag{13}$$

where γ_{00} is the overall mean across governorates or industries. The intra-class correlation coefficient (ICC) measures the correlation among the individual observations (firms) within clusters (governorates or industries). When the ICC equals 0, there is no difference between OLS regression estimates and those obtained with the multilevel modeling. Formally, the ICC is calculated by the ratio of the between cluster variance to the total variance:

$$\rho = \sigma_{u_0}^2 / \left(\sigma_{u_0}^2 + \sigma_e^2 \right) \tag{14}$$

The model in (Eq. 13) can be extended to consider both individual and regional or industrial factors. A separate regression model is defined in each level:

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + e_{ij} \tag{15}$$

where X_{ij} is an exploratory variable at the lowest level (firm). The variation of the regression coefficients β_j is modeled by a group-level regression model (governorate or industry):

$$\beta_{0j} = \gamma_{00} + \gamma_{01} Z_j + \mu_{0j} \quad \text{and} \quad \beta_{1j} = \gamma_{10} + \gamma_{11} Z_j + \mu_{1j} \tag{16}$$

Thus, the combined model follows:

$$Y_{ij} = \gamma_{00} + \gamma_{10} X_{ij} + \gamma_{01} Z_j + \gamma_{11} X_{ij} Z_j + (\mu_{0j} + \mu_{1j} X_{ij} + e_{ij}) \tag{17}$$

The deterministic part on the model, $\gamma_{00} + \gamma_{10} X_{ij} + \gamma_{01} Z_j + \gamma_{11} X_{ij} Z_j$, contains all the fixed coefficients, while the stochastic component is in brackets. The individual or firm level residuals e_{ij} are assumed to have a normal distribution with mean zero and variance σ_e^2. The group-level (regional or industrial level) $\mu_{0j} + \mu_{1j}$ are assumed to have a multivariate normal distribution with an expected value of zero, and they are assumed to be independent of the individual-level residuals e_{ij} (Van Oort et al. 2012). The variances of the residual errors μ_{0j} and μ_{1j} are specified as $\sigma_{u_0}^2$ and $\sigma_{u_1}^2$.

4 Results

4.1 Empty model results

We start our analysis by fitting a two-level empty model of firm nested within governorates or sectors. We test two different specifications, A and B, of Eq. 13. In A, we have governorate as level 2 and firm as level 1. In specification B, we take sector as level 2 and firm for the first level. The purpose of this step is to test for significant intercept variance, which is a test of the need for mixed modeling. If the intercept variance is not significant, it can be fixed for future steps. For both specifications, we

Table 4 Descriptive statistics of dependent and independent variables

	Type	Mean	SD (range)
Dependent variables			
Log of total factor productivity	Continuous	2.377	0.793 (−4.885 to 7.087)
Log of labor productivity	Continuous	8.929	0.937 (1.957–13.422)
Independent variables: individual level			
Log of age	Continuous	2.401	0.901 (0–4.997)
Log of size	Continuous	4.101	1.129 (1.792–8.431)
Log of age square		6.577	3.940 (0–24.972)
Log of size square		18.093	9.566 (3.210–71.074)
Log of capital intensity (lncapital)	Continuous	9.430	1.437 (1.779–13.853)
Log of R&D	Continuous	3.096	4.257 (0–14.866)
FDI	Dichotomous	0.311	
Human capital	Continuous	0.103	0.139 (0–1)
ICT (log of expenditure in ICT)	Continuous	10.506	2.091 (0–17.316)
Export	Dichotomous	0.423	
Independent variables: regional level			
Log of specialization	Continuous	−0.184	0.306 (−0.784 to 0.490)
Log of diversity	Continuous	0.906	0.415 (0–1.574)
Intra-governorate wage inequality (Gini index)	Continuous	0.326	0.056 (0–0.622)
Log of population density	Continuous	5.536	1.043 (1.335–7.897)
Log of industrial density	Continuous	5.082	0.585 (1.987–5.651)
% of FDI investment in the governorate	Continuous	0.245	0.121 (0–0 .399)
Volatility	Continuous	0.152	0.089 (0.004–0.496)
Educational level (% university education)	Continuous	0.081	0.021 (0.024–0.116)
Unemployment rate (%)	Continuous	0.144	0.032 (0.092–0.275)
Independent variables: industrial level			
Industry agglomeration (EG index)	Continuous	0.037	0.037 (−0.019 to 0.175)
Intra-sector wage inequality (Gini index)	Continuous	0.324	0.048 (0.235–0.442)
Industrial volatility	Continuous	0.156	0.080 (0–0.384)
N (governorates)	22		
N (sectors)	6		
N (years)	7		
N (firms)	9062		

use the maximum likelihood methods [the maximum likelihood (ML) and restricted or residual maximum likelihood estimation (REML)] to obtain estimates of the empty model (Eq. 13). It is well known in the multilevel modeling literature that variance components based on the ML estimation are negatively biased, when the REML estimation is not (Schabenberger and Pierce 2010).

The results of ML and REML are shown in Table 5, where we report the second level intercept, γ_{00}, its variance, $\sigma^2_{u_0}$, and the variance of the lowest level, σ^2_e. We have also included the intra-class correlation (ICC) and the likelihood ratio test (LR) to compare the mixed model to the linear regression model.

Table 5 Empty model

	Level 2: governorate		Level 2: sector	
	MLE	REML	MLE	REML
Constant (γ_{00})	2.279***	2.278***	2.328***	2.328***
Standard error	0.039	0.040	0.072	0.079
$\sigma^2_{u_0}$	0.024***	0.027***	0.030***	0.037***
Standard error	0.012	0.014	0.018	0.024
σ^2_e	0.620***	0.620***	0.612***	0.612***
Standard error	0.009	0.009	0.009	0.009
ICC = $\sigma^2_{u_0}/(\sigma^2_{u_0}+\sigma^2_e)$	0.038	0.042	0.047	0.056
LR chi(2)	81.12***	84.27***	226.93***	231.37***
Log of likelihood	−11,185	−11,187	−11,111	−11,113
BIC	22,397	22,401	22,251	22,254

*, **, *** are significant at 10%, 5% and 1%, respectively

Table 5 shows that the estimates obtained from MLE and REML are very similar and sometimes equivalent. The LR tests indicate that mixed multilevel model is more appropriate than simple linear model (the LR tests are significant at the 0.01 level), which allows us to justify the use of the multilevel modeling approach. The ICCs indicate that 4% and 6% of the variability of firm-level productivity are due, respectively, to regional and industrial variations. So, the second level (regional or industrial) has a significant role on the firm's TFP, but it is minor compared to the firm's characteristics.

4.2 Fixed effects results with both firm and contextual characteristics

The results regarding the impact of firm characteristics on TFP by using REML are shown in Table 6 (column 1). We also include year dummies and industry dummies to control for fixed effects introduced, respectively, by time and sector classification (column 2 in Table 6). The results show that almost all firm-level explanatory variables (the fixed effects) have significant coefficients. The results in columns 1 and 2 suggest that size in terms of employment and age have a negative impact on TFP. However, for our sample where data on exiting firms are not available, the size and age variables have to be interpreted with caution. Hence, young firms tend to be smaller and less efficient than older and larger ones. This is consistent with the finding that new firms generally enter with low productivity levels in comparison with the existing firms. When controlling for nonlinear effects of firm's size and firm's age by using its square, only the effect of the age square on TFP becomes positive and significant at 1%. This positive relationship between productivity and age square can be explained by the fact that new firms need time to accommodate to the situation within which they operate (learning effects) in order to increase their productivity. These results show that the oldest small firms are more productive than larger firms.

The estimated elasticity of R&D expenditure variable is significant at 1%. An increase in R&D expenditure of 10% would increase the firm's TFP by nearly

Table 6 Hierarchical multilevel regression models of firm TFP

	Model (2)		Model (2) + Regional factors		Model (2) + Industrial factors	
	(a)	(b)	(a)	(b)	(a)	(b)
Firm characteristics (first level)						
Log of age	−0.1573***	−0.094**	−0.150***	−0.095**	−0.142***	−0.111***
Log of size	−0.404***	−0.327***	−0.391***	−0.317***	−0.321***	−0.318***
Log of age square	0.037***	0.021**	0.038***	0.021**	0.032***	0.026***
Log of size square	0.010*	0.004	0.009*	0.003	0.003	0.003
Log of capital intensity	−0.204***	−0.218***	−0.202***	−0.219***	−0.213***	−0.213***
Log of R&D	0.015***	0.014***	0.015***	0.013***	0.015***	0.015***
FDI	0.300***	0.285***	0.302***	0.286***	0.273***	0.272***
Human capital	0.762***	0.707***	0.767***	0.712***	0.751***	0.747***
ICT	0.070***	0.064***	0.069***	0.065***	0.063***	0.063***
Export	0.114***	0.178***	0.113***	0.176***	0.159***	0.157***
Regional characteristics (level 2)						
Log of specialization			0.009	0.075		
Log of diversity			−0.010	0.016		
Gini			0.894***	0.394*		
Log of population density			−0.001	0.010		
Log of industrial density			0.062**	0.067**		
% of FDI firms			−0.359**	−0.437***		
Volatility			−0.148	0.099		
Human capital			1.517	1.576*		
Unemployment			−0.279	−0.407		
Coastal zone					0.125**	0.116**
Industrial characteristics (level 2)						
Gini					1.190***	−0.628
Agglomeration					0.374	0.909
Volatility					−0.006	−0.389
Constant	4.921***	4.803***	4.346***	4.346***	4.402***	4.918***
BIC	13,468	13,162	13,477	13,205	13,349	13,208
Log likelihood	−6676	−6475	−6641	−6456	−6599	−6502
N	7057	7057	7057	7057	7057	7057
R squared (level 1)	0.294	0.324	0.313	0.348	0.278	0.291
R squared (level 2)	0.554	0.488	0.686	0.702	0.513	0.403

*, **, *** are significant at 10%, 5% and 1%, respectively

0.15%. The estimates show also that FDI has a positive impact on the firm's performance. This finding is in line with those of recent studies (Raspe and van Oort 2011; Amara and El Lahga 2015). The estimated coefficient of the human capital is significant and has a correct sign as usually found in the literature. Like in the case of R&D, an increase in human capital affects the ability of firms to learn and absorb new information. In addition, we found that firms operating in ICT industries display better TFP. Firms in a high-technology environment are more likely to absorb new developments quickly and to boost productivity additionally.

Our results show also that exporters are more productive than non-exporters. Indeed, trade liberalization induces greater competitive pushing firms to improve their productivity to remain active in the export markets. There are two alternative hypotheses on why exporters can be expected to be more productive than non-exporting firms: self-selection and learning-by-exporting (Bernard and Jensen 1999; Bernard and Wagner 1997). The first hypothesis refers to self-selection on the more productive firms into export markets. The additional costs of selling goods in foreign markets, the existence of sunk costs associated with selling abroad and fiercer competition in international markets provide an entry barrier that solely the successful firms can overcome. The second hypothesis refers to the role of learning-by-exporting and states that exporting makes firms more productive. Indeed, trade promotes knowledge transfer and provide an incentive for innovation. The exporting firms could then benefit from technologies, superior management practices and the exploitation of economies of scale induced by multiple foreign markets, and therefore productivity will be increased.

In Table 6, we also combine the firm-level variables with the governorate-level variables in order to predict the firm performance (column 3 and column 4). Among the governorate-level variables, the

Log of industrial density (capturing agglomeration effects) has a statistically significant positive effect on TFP. Ciccone and Hall (1996) have tried to explain the positive relationship between firm performance and industrial density. They argued that industrial density promotes productivity through externalities associated with physical proximity. In addition, the production of all goods within a particular geographical area can reduce transportation cost and improve productivity. By using the multilevel analysis that seriously considers micro–macro-linkages of firms in their spatial and sectoral contexts, we can explicitly clarify the importance of agglomeration economies to the performance of firms. Indeed, many studies using aggregated regional-level data provide only limited insights and weak support for the effects of agglomeration economies on firm performance (Van Oort et al. 2012).

An increase in the regional level of FDI would decrease the productivity level of the firm through negative spillovers. Indeed, the governorate is composed by firms from different sectors that can show a strong gap in terms of skilled workers and technology. Hence, educational and technological gaps between firms in the same governorate may have a negative impact on the firm’s performance and reduce, consequently, the capability to absorb spillovers. Similar results for the FDI are also found by Baccouche et al. (2008), Grima (2005) and Amara and El Lahga (2015). Baccouche et al. (2008) show, for example, that FDI spillovers can only be beneficial for companies with high absorption capacity and that Tunisian manufacturing firms are considered to have high absorptive capacity if they are operating close to the industry frontier. Girma (2005) argues that FDI-related productivity gains initially increase at an increasing rate, but the rate diminishes as the absorptive capacity of domestic firms rises.

Regional wage disparities approximated by the Gini index have a positive impact on firm performance. Wage differences across areas can reflect differences in workers skills and technology.[11] Combes et al. (2008) show that up to half of the spatial wage disparities can be traced back to differences in the skill composition of the workforce. In addition, they show that location matters for urban workers wages and larger cities would improve efficiency. As a result, TFP can be higher in cities where firms benefit from agglomeration externalities that increase the labor efficiency of their workers. The coefficient of regional wage disparities becomes insignificant at 5% level when controlling for sector classification.

The last two columns of Table 6 present the results of the hierarchical multilevel regression model with the sector as the second level. We use the 'coastal zone' variable that takes 1 if the firm is located at the coastal area and 0 otherwise to control for the spatial location effect. As we can see, firms from the coastal zone are more productive than those from lagging areas.

4.3 Fixed effects results with both firm, contextual and cross-level interactions

Another way to consider the effects of the regional or industrial variables is to examine their cross-level interaction effects. We examine whether a regional or sector variable has an effect on the productivity slopes of the firm (indirect effects). Table 7 presents the results of the interaction between contextual level (regional or sector) and firm characteristics such as age, size, human capital, and R&D. No significant cross-level interaction between governorate and firm was found. However, we find that the interaction effects between firm characteristics (age, size, human capital, and R&D) and industrial variables (industrial agglomeration and intra-industry wage differentials) are all significant and positive at 5% level. The negative effects of age and size on firm's TFP become positive when the industrial agglomeration increases. From Table 7 (columns 3 and 4), we can see that the direct effect of industrial agglomeration is negative and significant at the 1% level. This finding of a negative industrial agglomeration effect can be explained by the fact that Tunisian manufacturing firms are less competitive. The positive interaction effects between industrial agglomeration (level 2) and firm's size and firm's age (level 1) show that agglomeration externalities are beneficial spillover effects for larger and older firms. So industrial agglomeration matters, however, the impact here is not with regard to its direct effect on TFP (which is negative), but with respect to its interaction effect.

The positive effect of human capital on TFP becomes stronger when the Gini coefficient measuring the intra-industry wage differentials increases (the coefficient of the interaction effects for intra-industry wage gap by human capital). This result would be in line with sorting theories, according to which the quality of the human capital has an impact on productivity. Having schooled workers makes everyone more productive, raising the firm's wage level which explains the intra-industry wage differentials. In addition, we find that the positive effect of the R&D becomes stronger when the intra-industry wage gap increases.

[11] We performed a granger causality test in order to study the causal relationship between regional wages and productivity. The results show that no causal relationship exists between regional wages and productivity (Stata code and results can be provided by the authors upon request).

Table 7 Hierarchical multilevel regression models of firm TFP with interaction terms

	2 Level + interaction		2 Level + interaction	
	Time and sector		Time and sector	
Independent variables: individual level				
Log of age	−0.120**	−0.086*	−0.147***	−0.114***
Log of size	−0.368***	−0.272***	−0.362***	−0.365***
Log of age square	0.035***	0.020**	0.025***	0.018*
Log of size square	0.012*	0.007	0.005	0.005
Log of capital intensity	−0.203***	−0.219***	−0.215***	−0.216***
Log of R&D	0.015***	0.013***	−0.043***	−0.048***
FDI	0.303***	0.291***	0.273***	0.272***
Human capital	0.759***	0.702***	−0.456	−0.522
ICT	0.069***	0.064***	0.063***	0.063***
Export	0.108***	0.169***	0.157***	0.155***
Independent variables: regional level				
Log of specialization	0.001	0.187		
Log of diversity	0.079	0.212		
Gini	0.879***	0.379*		
Log of population density	−0.003	0.009		
Log of industrial density	0.064**	0.072***		
% of FDI firms	0.293	0.176		
Volatility	−0.154	0.083		
Human capital	1.571	1.581*		
Unemployment	−0.282	−0.413		
Coastal zone			0.123**	0.114**
Interaction terms				
Size * diversity	−0.020	−0.045		
Size * specialization	0.001	−0.026		
Size * FDI	−0.098	−0.136		
Age * FDI	−0.105	−0.030		
Independent variables: industrial level				
Gini			0.155	−1.743***
Agglomeration			−4.152***	−3.919***
Volatility			−0.004	−0.365
Interaction terms				
Size * agglomeration			0.528**	0.602**
Age * agglomeration			0.955***	0.942***
Human capital * Gini			3.557**	3.750**
R&D * Gini			0.178***	0.194***
Constant	4.150***	4.087***	4.968***	5.521***
BIC	13,508	13,234	13,324	13,174
Log-likelihood	−6639	−6453	−6569	−6467
N	7057	7057	7057	7057

Table 7 (continued)

	2 Level + interaction		2 Level + interaction	
	Time and sector		Time and sector	
R squared (level 1)	0.313	0.348	0.284	0.300
R squared (level 2)	0.687	0.703	0.526	0.455

*, **, *** are significant at 10%, 5% and 1%, respectively

4.4 Robustness analysis

In the core of the paper, we used TFP as a proxy of firm productivity level. However, it is difficult to decide if TFP is the most appropriate measure of firm's performance and it would be a good robustness check to estimate a multilevel mixed model using the labor productivity (LP) as a second proxy of firm performance.[12] Table 10 reports the result of the empty model by using the LP as the dependent variable. Compared to preview results reported in Table 5, the ICCs have increased by more than twice. About 10% and 16% of the variability of the firm-level labor productivity are due, respectively, to regional and sectoral variations. This result confirms again the utility of the multilevel analysis.

Table 11 reports the fixed effects results with both firm and contextual characteristics, where Table 12 added the cross-level interaction effects. It is easily seen that the results are very close to those under TFP (Tables 6, 7), except for the capital intensity variable which becomes significantly positive. The opposite sign of this variable can be caused by the complementarity between labor and capital. Indeed, when we use a partial productivity or single-factor productivity (e.g. LP), qualitative and quantitative changes in one factor can heavily impact the partial productivity of the other factor. It is also possible, during an important investment in capital goods, that labor productivity increased but the total factor productivity remains unchanged or even decrease given the investment cost.

5 Conclusion and policy implications

While most of the existing studies on firm productivity in Tunisia focused on the micro-aspects, the present study is the first to demonstrate the joint contribution of contextual-level (regional and sectoral) and individual-level firm's characteristics on firm's performance. To do this, we combine a dataset of Tunisian manufacturing firm with regional and sectoral variables and apply a multilevel analysis in order to discern the contextual effect of firm's on its productivity level, after taking into account its individual characteristics.

[12] Sargent and Rodriguez (2000) argued that the choice between the TFP and the LP should depend on several factors such as the time period of interest, the quality and comparability of the capital stock data and the growth model assumed. They indicated that the LP is more appropriate for a short period (a period of a decade or so), while the TFP should be used in the case of long-run trends of several decades.

Three main results can be derived from our analysis. The first is that firm characteristics greatly impact on both total factor productivity and labor productivity. More specifically, we find that about 95% of firms' TFP is explained by internal firm characteristics, while the macro-level (regional or sectoral) effects just explain 5% of firms' productivity, and that sectors play a more prominent role that region. This result confirms that the main sources of firm performance are different at the individual level. We find that the oldest small firms are more productive than larger firms. Results indicate that firms with a higher level of human capital, R&D expenditure, and FDI perform better in terms of productivity. We also found that firms operating in ICT industries and exporting firms are more productive. In this context, special stress must be placed on human capital and R&D expenditure to improve firms' performance.

Secondly, the positive and significant relationship between firms' productivity and industrial density at the governorate level clearly shows the essential role of location and contextual effects in promoting firms' performance. The results of the ICCs and LR tests confirm the existence of significant between-governorate variation in TFP and LP that was not explained by individual firm level factors. We found that the governorate contributes almost 4% to TFP at the firm level. This seems modest, but the governorate contributions represent 10% when using labor productivity as a dependent variable. The positive and significant relationship between inter-firm wage dispersion and firm productivity provides evidence of technological gap and human capital intensity between sectors in the same governorate.

Finally, our results show that when we consider sector as the second level, the direct effects of sectoral variables are not significant. However, we find positive and significant interaction effects (indirect effects) of those variables through firm characteristics (age, size, human capital, and R&D). We find that the coefficient of the interaction effects for intra-industry wage gap by human capital is positive and significant. In addition, we find that the positive effect of the R&D becomes stronger when the intra-industry wage gap increases. The negative effects of age and size on firm's TFP become positive when the industrial agglomeration increases.

Our results have important policy implications as well. One, the result shows that exportation, human capital, ICT and R&D generally benefit TFP and LP. This means that government needs to implement measures that aim to consolidate the export volume, improve terms of trade to increase access to foreign capital, and advocate investment in human capital to enhance the absorptive capacity in order to facilitate technology transfer. Our results show also that sectors matter more than the region; so it is necessary for the government to implement industrial policies. The reconsideration of competitiveness poles, covering the key sectors, such as mechanical and electrical industries, textiles-leather and footwear, agro-food and ICT, is one of these policies. These poles generate a competitive atmosphere, support the culture of innovation, and stimulate the transfer of knowledge and technologies between firms, workers, and universities.

Appendix

See Fig. 1; Tables 8, 9, 10, 11 and 12.

Fig. 1 The 24 governorates of Tunisia: Greater Tunis (1: Tunis, 2: Ariana, 3: Ben Arous, 4: Manouba)

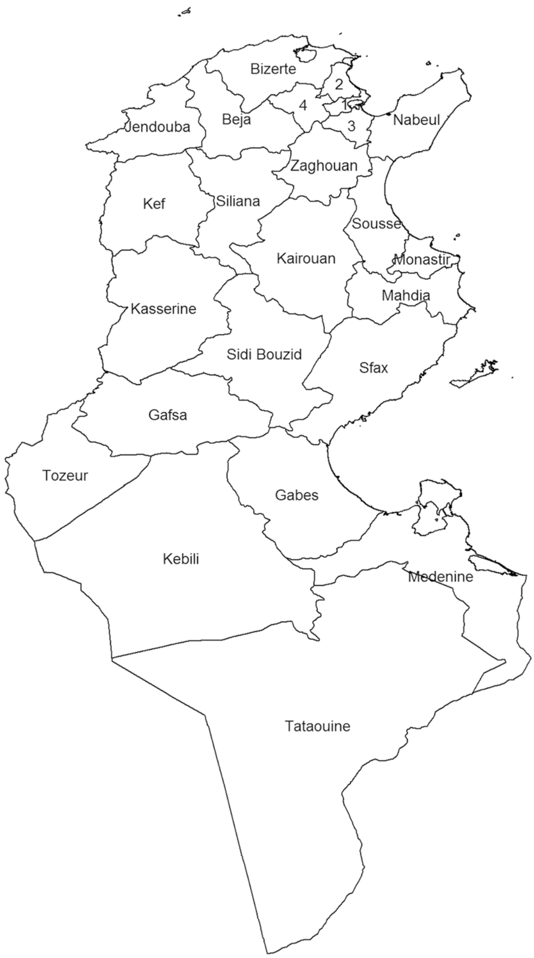

Table 8 TFP estimation

	IAA	ITHC	ICCV	IMME	ICH	ID	All sectors
Labor	0.407***	0.707***	0.559***	0.628***	0.419***	0.759***	0.636***
SE	(0.071)	(0.024)	(0.102)	(0.034)	(0.059)	(0.067)	(0.012)
Capital	0.370***	0.569***	0.681***	0.593***	0.562***	0.298***	0.586***
SE	(0.197)	(0.050)	(0.182)	(0.177)	(0.085)	(0.137)	(0.063)
CRS	0.777	1.276***	1.240	1.221	0.981	1.057	1.222***
Wald test of CRS (Chi2)	0.570	33.370	1.240	1.860	0.070	0.410	16.590
p value	[0.452]	[0.000]	[0.266]	[0.173]	[0.793]	[0.521]	[0.000]

CRS constant returns to scale

*, **, *** are significant at 10%, 5% and 1%, respectively

Table 9 TFP and LP distributions by sector (annual averages 1998–2004 in log)

Sector	TFP	Rank	LP	Rank
IAA	4.853	2	9.460	2
ITHC	4.290	6	8.603	6
IMCCV	4.498	5	9.035	5
IME	4.618	3	9.182	4
ICH	5.028	1	9.692	1
ID	4.613	4	9.328	3
Total	4.498		8.957	

Table 10 Empty model using labor productivity

	Level 2: governorate		Level 2: sector	
	MLE	REML	MLE	REML
Constant	8.854***	8.853***	9.080***	9.080***
Standard error	0.066	0.067	0.139	0.153
$\sigma^2_{u_0}$	0.081***	0.086***	0.116***	0.139***
Standard error	0.029	0.031	0.067	0.088
σ^2_e	0.819***	0.819***	0.748***	0.748***
Standard error	0.012	0.012	0.011	0.011
ICC	0.090	0.095	0.134	0.157
LR chi(2)	590.60***	594.46***	1471.21***	1476.64***
Log likelihood	− 12,507	− 12,509	− 12,067	− 12,068
BIC	25,042	25,045	24,161	24,163

*, **, *** are significant at 10%, 5% and 1%, respectively

Table 11 Robustness checks (multilevel model using labor productivity)

	First level only		Level 1 and Level 2 (governorate)		Level 1 and Level 2 (sector)	
	Time and sector		Time and sector		Time and regional	
Independent variables: individual level						
Log of age	− 0.167***	− 0.094**	− 0.159***	− 0.095**	− 0.156***	− 0.111***
Log of size	− 0.159***	− 0.105*	− 0.150***	− 0.095*	− 0.086*	− 0.096*
Log of age square	0.039***	0.021**	0.038***	0.021**	0.035***	0.026***
Log of size square	0.009	0.004	0.008	0.003	0.002	0.003
Log of capital intensity	0.390***	0.368***	0.391***	0.368***	0.378***	0.373***
Log of R&D	0.016***	0.014***	0.016***	0.013***	0.015***	0.015***
FDI	0.303***	0.285***	0.301***	0.286***	0.275***	0.272***
Human capital	0.785***	0.707***	0.783***	0.712***	0.757***	0.747***
ICT	0.066***	0.064***	0.066***	0.065***	0.061***	0.063***
Export	0.128***	0.178***	0.125***	0.176***	0.170***	0.157***
Independent variables: regional level						
Log of specialization			0.059	0.075		
Log of diversity			0.027	0.016		

Table 11 (continued)

	First level only		Level 1 and Level 2 (governorate)		Level 1 and Level 2 (sector)	
	Time and sector		Time and sector		Time and regional	
Gini			0.623***	0.394*		
Log of population density			−0.001	0.010		
Log of industrial density			0.056**	0.067**		
% of FDI firms			−0.322**	−0.437***		
Volatility			−0.362***	0.099		
Human capital			1.677*	1.576*		
Unemployment			−0.208	−0.407		
Coastal zone					0.123**	0.116**
Independent variables: industrial level						
Gini					0.364	−0.628
Agglomeration					0.695	0.909
Volatility					−0.221*	−0.389
Constant	4.928***	5.011***	4.476***	4.555***	4.752***	5.126***
BIC	13,501.3	13,162	13,522	13,205	13,395	13,208
Log likelihood	−6693	−6475	−6664	−6456	−6622	−6502
N	7057	7057	7057	7057	7057	7057
R squared (level 1)	0.521	0.543	0.533	0.560	0.497	0.507
R squared (level 2)	0.770	0.739	0.839	0.848	0.902	0.862

*, **, *** are significant at 10%, 5% and 1%, respectively

Table 12 Robustness checks (multilevel model using labor productivity with interaction)

	2 Level + interaction		2 Level + interaction	
	Time and sector		Time and sector	
Independent variables: individual level				
Log of age	−0.132***	−0.086*	−0.162***	−0.114***
Log of size	−0.131**	−0.050	−0.129**	−0.143***
Log of age square	0.036***	0.020**	0.027***	0.018*
Log of size square	0.010*	0.007	0.004	0.005
Log of capital intensity	0.390***	0.367***	0.376***	0.371***
Log of R&D	0.016***	0.013***	−0.039***	−0.048***
FDI	0.302***	0.291***	0.275***	0.272***
Human capital	0.775***	0.702***	−0.403	−0.522
ICT	0.066***	0.064***	0.061***	0.063***
Export	0.120***	0.169***	0.168***	0.155***
Independent variables: regional level				
Log of specialization	−0.049	0.187		
Log of diversity	0.059	0.212		

Table 12 (continued)

	2 Level + interaction		2 Level + interaction	
	Time and sector		Time and sector	
Gini	0.610***	0.379*		
Log of population density	−0.002	0.009		
Log of industrial density	0.056**	0.072***		
% of FDI firms	0.320	0.176		
Volatility	−0.369***	0.083		
Human capital	1.728*	1.581*		
Unemployment	−0.221	−0.413		
Coastal zone			0.123**	0.114**
Interaction terms				
Size * diversity	−0.007	−0.045		
Size * specialization	0.024	−0.026		
Size * FDI	−0.103	−0.136		
Age * FDI	−0.093	−0.030		
Independent variables: industrial level				
Gini			−0.566	−1.743***
Agglomeration			−4.109***	−3.919***
Volatility			−0.202	−0.365
Interaction terms				
Size * agglomeration			0.549**	0.602**
Age * agglomeration			1.020***	0.942***
Human capital * Gini			3.431**	3.750**
R&D * Gini			0.169***	0.194***
constant	4.313***	4.295***	5.284***	5.729***
BIC	13,553	13,234	13,371	13,174
Log likelihood	−6661	−6453	−6592	−6467
N	7057	7057	7057	7057
R squared (level 1)	0.533	0.560	0.503	0.513
R squared (level 2)	0.839	0.848	0.911	0.874

*, **, *** are significant at 10%, 5% and 1%, respectively

References

Ackerberg D, Benkard CL, Berry S, Pakes A (2007) Econometric tools for analyzing market outcomes. Handb Econom 6:4171–4276

Aiello F, Pupo V, Ricotta F (2014) Explaining total factor productivity at firm level in Italy: Does location matter? Spat Econ Anal 9(1):51–70

Alker HR (1969) A typology of ecological fallacies. In: Dogan M, Rokkam S (eds) Social ecology. MIT Press, Boston, pp 69–86

Amara M, Ayadi M (2014) Local employment growth in the coastal area of Tunisia: spatial filtering approach. Middle East Develop J 6(2):255–284

Amara M, El Lahga A (2015) A note on MAR and Jacobs externalities in the Tunisian manufacturing industries. Lett Spat Resour Sci 8(2):151–167

Amara M, Thabet K (2012) Structure industrielle et développement local du littoral tunisien, 1998–2004. Mondes en développement 1:119–136
Andersson M, Lööf H (2011) Agglomeration and productivity: evidence from firm-level data. Ann Reg Sci 46(3):601–620
Audretsch DB, Feldman MP (1996) R&D spillovers and the geography of innovation and production. Am Econ Rev 86(3):630–640
Audretsch DB, Feldman MP (2004) Knowledge spillovers and the geography of innovation. Handb Reg Urban Econ 4:2713–2739
Aw BY, Chung S, Roberts MJ (2000) Productivity and turnover in the export market: micro level evidence from the Republic of Korea and Taiwan (China). World Bank Econ Rev 14(1):65–90
Aw BY, Chen X, Roberts MJ (2001) Firm-level evidence on productivity differentials and turnover in Taiwanese manufacturing. J Dev Econ 66(1):51–86
Baccouche R, Bouoiyour J, M'Henni H, Mouley S (2008) Dynamics of investments, changing industry and convertibility capital account: impacts of the measures of liberalization and compared experiences Tunisia-Morocco, Research Project No. FEM 32-04
Backman M (2014) Human capital in firms and regions: impact on firm productivity. Pap Reg Sci 93(3):557–575
Ballot G, Fakhfakh F, Taymaz E (2001) Firms' human capital, R&D and performance: a study on French and Swedish firms. Labour Econ 8(4):443–462
Beaudry C, Schiffauerova A (2009) Who's right, Marshall or Jacobs? The localization versus urbanization debate. Res Policy 38(2):318–337
Berger PG, Ofek E (1999) Causes and effects of corporate refocusing programs. Rev Financ Stud 12(2):311–345
Bernard AB, Jensen JB (1999) Exceptional exporter performance: cause, effect, or both? J Int Econ 47(1):1–25
Bernard AB, Wagner J (1997) Exports and success in German manufacturing. Rev World Econ 133(1):134–157
Bronzini R, Piselli P (2009) Determinants of long-run regional productivity with geographical spillovers: the role of R&D, human capital and public infrastructure. Reg Sci Urban Econ 39(2):187–199
Caselli F (2005) Accounting for cross-country income differences. Handb Econ Growth 1:679–741
Chemmanur TJ, Krishnan K, Nandy DK (2014) The effects of corporate spin-offs on productivity. J Corp Finance 27:72–98
Ciccone A, Hall RE (1996) Productivity and the density of economic activity. Am Econ Rev 86:54–70
Ciccone A, Peri G (2006) Identifying human-capital externalities. Theory with applications. Rev Econ Stud 73:381–412
Cingano F, Schivardi F (2004) Identifying the sources of local productivity growth. J Eur Econ Assoc 2(4):720–742
Combes PP (2000) Economic structure and local growth: France, 1984–1993. J Urban Econ 47(3):329–355
Combes PP, Duranton G, Gobillon L (2008) Spatial wage disparities: sorting matters! J Urban Econ 63(2):723–742
Del Gatto M, Di Liberto A, Petraglia C (2011) Measuring productivity. J Econ Surv 25(5):952–1008
Dettori B, Marrocu E, Paci R (2012) Total factor productivity, intangible assets and spatial dependence in the European regions. Reg Stud 46(10):1401–1416
Duranton G, Puga D (2004) Micro-foundations of urban agglomeration economies. Handb Regional Urban Econ 4:2063–2117
Easterly W, Levine R (2001) It's not factor accumulation: stylized facts and growth models. World Bank Econ Rev 15:177–219
Ellison G, Glaeser EL (1997) Geographic concentration in US manufacturing industries: a dartboard approach. J Polit Econ 105(5):889–927
Fazio G, Piacentino D (2010) A spatial multilevel analysis of Italian SMEs' productivity. Spat Econ Anal 5(3):299–316
Girma S (2005) Absorptive capacity and productivity spillovers from FDI: a threshold regression analysis. Oxf Bull Econ Stat 67(3):281–306
Glaeser EL, Laibson D, Sacerdote B (2002) An economic approach to social capital. Econ J 112(483):F437–F458

Hall BH, Mairesse J (1995) Exploring the relationship between R&D and productivity in French manufacturing firms. J Econom 65(1):263–293
Henderson V, Kuncoro A, Turner M (1995) Industrial development in cities. J Polit Econ 103(5):1067–1090
Javorcik BS (2004) Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages. Am Econ Rev 94(3):605–627
John K, Ofek E (1995) Asset sales and increase in focus. J Financ Econ 37(1):105–126
Jovanovic B (1982) Selection and the evolution of industry. Econ J Econ Soc 50(3):649–670
Ke S (2010) Agglomeration, productivity, and spatial spillovers across Chinese cities. Ann Reg Sci 45(1):157–179
Keller W, Yeaple SR (2009) Multinational enterprises, international trade, and productivity growth: firm-level evidence from the United States. Rev Econ Stat 91(4):821–831
Krugman P (1991) Increasing returns and economic geography. J Polit Econ 99(3):483–499
Levinsohn J, Petrin A (2003) Estimating production functions using inputs to control for unobservables. Rev Econ Stud 70(2):317–341
Lucas RB (1988) On the mechanics of economic development. J Monet Econ 22:3–42
Majumdar SK (1997) The impact of size and age on firm-level performance: some evidence from India. Rev Ind Organ 12(2):231–241
Marouani MA, Mouelhi R (2016) Contribution of structural change to productivity growth: evidence from Tunisia. J Afr Econ 25(1):110–132
Martin P, Mayer T, Mayneris F (2011) Spatial concentration and plant-level productivity in France. J Urban Econ 69(2):182–195
Moretti E (2004) Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data. J Econ 121:175–212
Olley SG, Pakes A (1996) The dynamics of productivity in the telecommunications equipment industry. Econometrica 64:1263–1297
Parisi ML, Schiantarelli F, Sembenelli A (2006) Productivity, innovation and R&D: micro evidence for Italy. Eur Econ Rev 50(8):2037–2061
Petrin A, Poi BP, Levinsohn J (2004) Production function estimation in stata using inputs to control for unobservables. Stata J 4(2):113–123
Raspe O, van Oort FG (2011) Firm heterogeneity, productivity and spatially bounded knowledge externalities. Socio Econ Plan Sci 45(1):38–47
Rice P, Venables AJ, Patacchini E (2006) Spatial determinants of productivity: analysis for the regions of Great Britain. Reg Sci Urban Econ 36(6):727–752
Robinson W (1950) Ecological correlations and the behavior of individuals. Am Sociol Rev 15:351–357
Romer PM (1990) Endogenous technological change. J Polit Econ 90:71–102
Rosenthal SS, Strange WC (2001) The determinants of agglomeration. J Urban Econ 50(2):191–229
Sargent TC, Rodriguez ER (2000) Labour or Total Factor Productivity: Do We Need to Choose? Int Prod Monit 1:41–44
Schabenberger O, Pierce FJ (2010) Contemporary statistical models for the plant and soil sciences. CRC Press, Boca Raton
Smit MJ, Abreu MA, de Groot HL (2015) Micro-evidence on the determinants of innovation in the Netherlands: the relative importance of absorptive capacity and agglomeration externalities. Pap Reg Sci 94(2):249–272
Snijders TAB, Bosker RJ (1999) Multilevel analysis: an introduction to basic and advanced multilevel modeling. Sage, London
Stoyanov A, Zubanov N (2012) Productivity spillovers across firms through worker mobility. Am Econ J Appl Econ 4(2):168–198
Thabet K (2015) Industrial structure and total factor productivity: the Tunisian manufacturing sector between 1998 and 2004. Ann Reg Sci 54(2):639–662
Van Oort FG, Burger MJ, Knoben J, Raspe O (2012) Multilevel approaches and the firm-agglomeration ambiguity in economic growth studies. J Econ Surv 26(3):468–491
Vernon Henderson J (2007) Understanding knowledge spillovers. Reg Sci Urban Econ 37(4):497–508
Wagner J (2007) Exports and productivity: a survey of the evidence from firm-level data. World Econ 30(1):60–82
Wakelin K (2001) Productivity growth and R&D expenditure in UK manufacturing firms. Res Policy 30(7):1079–1090

Yasar M, Raciborski R, Poi B (2008) Production function estimation in Stata using the Olley and Pakes method. Stata J 8(2):221–231