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Send correspondence to:
Mohamed Amara
Higher School of Economic and Commercial Sciences of Tunis, University of Tunis
Mohamed.amara.isg@gmail.com

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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 context. 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 Classifications: O4, L1, D2

Keywords: Agglomeration economies, Micro-macro link, Multilevel Analysis, Total Factor Productivity, Tunisia.

ملخص

في هذه الورقة، نستخدم نماذج متعددة المستويات لتحليل الخصائص الفردية والقطاعية والإقليمية التي قد تؤثر على إنتاجية العامل الإجمالية لشركات التصنيع التونسية للفترة 1998-2004. نتائجنا تظهر أن الخصائص الفردية للشركة يكون لها تأثير هام على الإنتاجية الكلية لعوامل الإنتاج والعمل على حد سواء. نجد أن أقدم الشركات الصغيرة أكثر إنتاجية من الشركات الكبرى. السياق الإقليمي له تأثير كبير ومباشر على أداء الشركات. وبشكل أكثر تحديدا، فالكثافة الصناعية لها تأثير إيجابي على الإنتاجية الكلية لعوامل الإنتاج. والتفاوت في الأجور البينية الصناعي هي مفيدة فقط للشركات مع رأس المال البشري العالي والبحث والتطوير. تظهر آثار التفاعل أيضا أن الشركات الكبرى والقديمة سوف تستفيد أكثر من التكتل الصناعي. نخلص إلى أن النماذج متعددة المستويات أفضل لأنها تجمع بين خصائص ثابتة والسياق في وقت واحد، لأنها تسمح بخصائص الشركة معينة لتكون مرتبطة بشكل مختلف مع السياقات الإقليمية والقطاعية.

1. Introduction

There is a wide consensus on the necessity of understanding productivity growth in order to reduce the efficiency gap and to insure the convergence of productivity among industries and regions. This interest was largely motivated by recent empirical literatures 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 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; Cicone and Peri, 2006; Bronzini and Piselli, 2009; Andersson and Lööf, 2011).

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). 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 the 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 that form the core of economic activity represent 85% of the national GDP (World Bank, 2014). 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 multicolinearity problems so critical in empirical studies that rely on aggregate data only to investigate the relevance of the socio-economic context for economic activity (Fazio and Piacentino, 2010). Moreover, the multilevel analysis allows the inclusion of macro level (regional and/or sectoral) explanatory 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.

To the best of our knowledge, our study is the first to consider micro and macro interaction to examine the productivity of Tunisian manufacturing firms. It differs from the previous ones in several respects. Based on multilevel analysis, it analyses the influence of regional characteristics such as specialization, diversity and regional wage disparities on firm-level performance. In addition, it tests how sectoral specificities (such as the intra-industry wage differentials, the industrial volatility and the industrial agglomeration) affect firms' capabilities of being productive. 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) 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 use a sample of manufacturing Tunisian firms to distinguish between the effects of own firm's characteristics (direct effects) and mean characteristics of their neighbors (endogenous and contextual effects) on its output level. Thabet (2015) propose to analyze the impact of industrial structure on regional economic growth measured by total factor productivity using a panel of manufacturing firms operating in 138 delegations across the Tunisian coast and observed over the 1998–2004 period. 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. 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.

The remainder of the paper is organized as follows: to begin, we briefly conduct in section 2 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. Section 3 presents the data and the methodology employed to estimate the contribution of each micro-level and macro-level factor on the firm-level TFP. At last, we present, in the fourth section, an overview of the principal results and we summarize our thinking and attempt to suggest some policy recommendations to deciders in conclusion.

2. Firm Productivity and Regional Disparity in Tunisia: A Brief Review

In the literature reviews, productivity is considered at two different levels: the micro level and the macro level. In micro-level, and giving 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 United States, Germany, France, Italy and the United Kingdom (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, 2013). Human capital can impact firm's performance through several mechanisms (Ballot et al, 2001): (1) a firm who 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 suggested 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 (approximated by the age of the firm) are important for firm-level productivity (Majumdar, 1997; Raspe and Van Oort; 2011).

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; 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 and social networks lead to better firm performance, such as productivity levels (Ciccone and Hall 1996; Cingano and Schivardi 2004).

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 economics. 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* stated also that 'Markets favor some places over others, some places-cities, coastal area, and connected countries are favored by producers' (World Bank, 2009).

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, which have been reinforced by the impact of distortive economic policies (World Bank, 2014). 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 regions 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 mean (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).[1] 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 value added or zero investment. The dataset includes: value added, investment, firm's birth date, capital stock, foreign capital participation, expenditure in information and communication technology, expenditure in R&D, exporting rate and labour (number of employees). The number of employees contains the number of engineers and managers used to approximate the human capital.

On average, in each year there are only 13 firms that employed at least thousand workers which represents no more than 1% of all firms. However, these firms account for more than a quarter of all employment and are also the oldest with an average age of 25 years.

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 robustness check, we use the labor productivity (measured as value added by worker) as the second dependent variable.[2] 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 given by:

$$y_{it} = a_0 + a_k k_{it} + a_l l_{it} + u_{it} \qquad (1)$$

$$u_{it} = \omega_{it} + \eta_{it}$$

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 labour 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

[1] The INS collects annual unbalanced-sheet data on a sample of 5000 firms covering almost all formal sectors (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 conducting by the INS every five years since 1997. The national register of establishments that is continuously updated provides a safe basis for the sampling of both surveys.

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

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, 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.[3] Second, if no allowance is made for firm entry and exit, a selection bias will emerge. In this paper we don't treat the selection bias by using firm-level data because we do not have accurate information on entry and exit decisions.[4] We only consider the simultaneity bias and we chose to apply the structural approach proposed in Olley and Pakes (1996) to solve this problem.[5] 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 no exit (firm continuous in operation), investment is a function of current state variables.

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

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

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

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:

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

Where $\phi(i_{it}, k_{it}) = a_0 + a_k k_{it} + h_t(i_{it}, k_{it})$ 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:

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

[3] 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.

[4] Note that the selection bias emerges once the selection process is not random. Or we have not exact information about the reason of 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.

[5] There exist many other approach that correct the endogeneity problem like those proposed in Levinsohn and Petrin (2003) and Ackerberg et al. (2007) but we don't use this approach because we don't dispose observation on intermediate input which constitute a basic variable for these methods.

where ξ_{it} is an innovation with zero mean uncorrelated with k_{it} ($E(\xi_{it}|k_{it}) = 0$). 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):

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

Once the production function parameters have been estimated, one can infer the total factor productivity using the following formula:[6]

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

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 ($R\&D_{ij}$) (Mairesse and Sassenou 1991, Hall and Mairesse 1995). Human capital (H_{ij}), foreign direct investment (FDI_{ij})[7] and capital intensity ($capital_{ij}$) 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 capture 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 Hirshman-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:

$$SPEC_j = \sum_s \left| \frac{emp_{js}}{emp_j} - \frac{emp_j}{emp} \right| \tag{8}$$

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.

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

$$DIV_j = 1 \,/\, (\textstyle\sum_s (\frac{emp_{js}}{emp_j})^2) \tag{9}$$

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[6] 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 table A1 and A2 of the Appendix.

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

DIV_j =1 if economic activity in the governorate under consideration is fully concentrated in one industry and increases as activities in 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 ($Gini\_wage_j$) to measure the regional wage disparities across governorates.

We also suppose that the presence of the 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 other. A high rate of firm turnover can positively affect the 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 ($volatility_j$) defined as: [8]

$$volatility_j = \left(entry\ rate_j + exit\ rate_j\right) - \left|entry\ rate_j - exit\ rate_j\right| \qquad (10)$$

It is the sum of the entry and exit rate minus the absolute value of the net entry rate at the governorate level.[9]

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 1,000 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 to generating information spillovers within region. Following22most 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 the 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 industrial structure from concentration arising from agglomerative externalities (Rosenthal and Strange, 2001). Indeed, industrial concentration can be due simply to the existence of a small number of large plants and that there is no agglomeration force. To address this problem,

[8] 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.

[9] 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.

Ellison and Glaeser propose the following agglomeration index to measure the degree of the sth industry's agglomeration at the regional level:

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

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-Hirschmann 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.

$$volatility_s = (entry\ rate_s + exit\ rate_s) - |entry\ rate_s - exit\ rate_s| \quad (12)$$

3.3 Methodology

In this study, we employed multilevel modelling that exploits the hierarchical structure of the data in order to determine the direct effect of individual (firm) and group (governorate or sector) explanatory variables, as well as the interactions between them (Snijders and Bosker 1999; Goldstein 2011). 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 random intercept-only model or null model, is modelled as:

$$Y_{ij} = \gamma_{00} + \mu_{0j} + e_{ij} \quad (13)$$

Where γ_{00} is the overall mean across governorates or industries. The intraclass 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 modelling. Formally, the ICC is calculated by the ratio of the between cluster variance to the total variance:

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

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:

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + e_{ij} \quad (15)$$

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

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

Thus, the combined model follows:

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

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 from 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 $\sigma^2_{u_0}$ and $\sigma^2_{u_1}$.

4. Estimation 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 equation 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 modelling. If the intercept variance is not significant, it can be fixed for future steps. For both specifications, we use the maximum likelihood methods (the maximum likelihood (ML) and restricted or residual maximum likelihood estimation (REML)) to obtain estimates of the empty model (equation 13). It is well known in the multilevel modeling literature that variance components based on the ML estimation are negatively biased, where 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 mixed model to the linear regression model.

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 modelling 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 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 productivity levels lower than that of the existing firms. When controlling for non-linear 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 firm's TFP by nearby 0.15%. The estimates show also that FDI has a positive impact on 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 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 the 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 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); Thabet (2015) 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. 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 hierarchical multilevel regression model with sector as 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 the 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.

4.4 Robustness analysis

In the body 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 robustness check to estimate a multilevel mixed model using the labor productivity (LP) as a second proxy of firm performance.[10] Table A3 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 A4 reports the fixed effects results with both firm and contextual characteristics, where Table A5 added the cross-level interaction effects. It is easily seen that the results are very close to those under TFP (Table 6 and Table 7), except for the capital intensity variable which becomes significantly positive. The opposite sign of this variable can be caused by the complementarily of the two primary inputs of production. Indeed, when we use a partial productivity or single-factor productivity (eg. LP), qualitative and quantitative changes in one factor can heavily impact the partial productivity of the other factor. It is also possible, during

[10] 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 decade or so), while the TFP should be used in the case of long run trends of several decades.

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 data-set 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.

Three main results follow from our analysis. The first is that firm characteristics greatly impact in 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 differences at individual level. At this 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 attention 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 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 by 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 exports, human capital, ICT and R&D generally benefit TFP and LP. This means that government needs to implement measures that aim to increasing the export volume, improving terms of trade to increase access to foreign capital, and increasing investment in human capital to enhance the absorptive capacity in order to facilitate technology transfer. Our results show also that sectors matter much than region, so it is necessary for the government to apply industrial policies. The installation of competitiveness poles covering the key sectors such as mechanical and electrical industries, textiles-leather and footwear, agrofood 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.

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Table 1: Firm Size and Employment Distributions (annual averages 1998–2004)

Size category	# of	% of	# of jobs	% of	Age
# of workers	Firms	Firms		employment	(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%	10834	6.86%	18.40
[50, 99]	294	21.95%	20892	13.22%	17.15
[100, 199]	280	20.95%	39175	24.79%	19.09
[200, 999]	182	13.58%	62503	39.56%	20.98
≥1000	13	00.94%	21672	13.72%	25.22
Total	1338		158012		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	14169	8.97
ITHC	654	48.86	86178	54.54
IMCCV	105	07.84	10813	6.84
IME	228	17.04	28288	17.90
ICH	70	05.24	9700	6.14
ID	116	08.66	8883	5.61
Total	1338		158012	

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	47468	30.04
North-East	247	18.47	35101	22.21
North-West	17	01.27	2633	01.67
Center-East	663	49.56	68067	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		158012	

Table 4: Descriptive Statistics of Dependent and Independent Variables

	Type	Mean	stdv (range)
Dependent variables			
log of Total Factor Productivity	Continuous	2.377	0.793 (-4.885 - 7.087)
log of Labour 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 - 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 - 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	

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 likelihhod	-11185	-11187	-11111	-11113
BIC	22397	22401	22251	22254

Notes: *** significant at 1% level.

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		
			Industrial characteristics (level 2)			
Gini					1.190***	-0.628
Agglomeration					0.374	0.909
Volatility					-0.006	-0.389
Coastal zone					0.125**	0.116**
Constant	4.921***	4.803***	4.346***	4.346***	4.402***	4.918***
BIC	13468	13162	13477	13205	13349	13208
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

Table 7: Hierarchical Multilevel Regression Models of Firm TFP with interaction terms

	2 level + interaction	time and sector	2 level + interaction	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		
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
Coastal zone			0.123**	0.114**
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	13508	13234	13324	13174
Log likelihood	-6639	-6453	-6569	-6467
N	7057	7057	7057	7057
R squared (level 1)	0.313	0.348	0.284	0.300
R squared (level 2)	0.687	0.703	0.526	0.455

Appendix

Figure 1: The 24 Governorates and the 7 Regions of Tunisia: Greater Tunis (1, 2, 3 and 4); North-East (5, 6 and 7); North-West (8, 9, 10 and 11); Center-West (12, 13 and 14); Center-East (15, 16, 17 and 18); South-West (19, 20 and 21); South-East (22, 23 and 24).

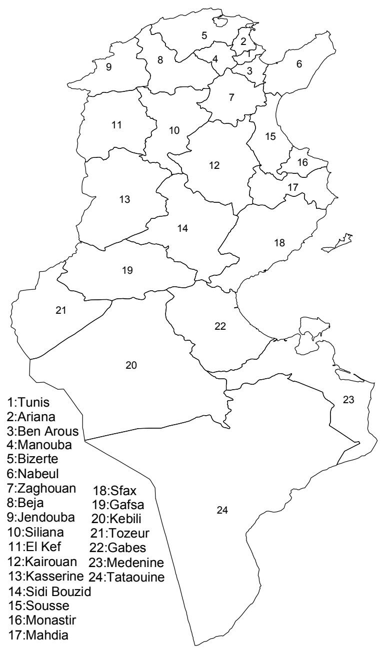

Table A1: TFP Estimation

	IAA	ITHC	ICCV	IMME	ICH	ID	All sectors
Labour	0.407***	0.707***	0.559***	0.628***	0.419***	0.759***	0.636***
Std. Err.	(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***
Std. Err.	(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]

Notes: CRS: constant returns to scale;

Table A2: 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 A3: 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
U	0.081***	0.086***	0.116***	0.139***
standard error	0.029	0.031	0.067	0.088
Epsilon	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***
LL	-12507	-12509	-12067	-12068
BIC	25042	25045	24161	24163

Table A4: Robustness Checks (Multilevel Model Using Labor Productivity)

	First level only	time and sector	level 1 and Level 2 (governorate)	time and sector	level 1 and Level 2 (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***	-.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		
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		
Independent variables: Industrial level						
Gini					0.364	-0.628
Agglomeration					0.695	0.909
Volatility					-0.221*	-0.389
Coastal zone					0.123**	0.116**
Constant	4.928***	5.011***	4.476***	4.555***	4.752***	5.126***
BIC	13501.3	13162	13522	13205	13395	13208
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

Table A5: Robustness Checks (Multilevel Model Using Labor Productivity)

	2 level + interaction	time and sector	2 level + interaction	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		
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		
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
Coastal zone			0.123**	0.114**
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	13553	13234	13371	13174
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