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RESEARCH ARTICLE

Unemployment and Coordination Failures in Tunisia: Estimation Using Stochastic Frontier Analysis

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Abstract

In studying the unemployment-coordination failure relationship, we adopted a regional labor market analysis to understand the role of regional disparities in the persistently high unemployment rate through a matching process. We included some additional variables as drivers of matching efficiency and regional disparities. For this purpose, we performed a stochastic frontier analysis for 24 regions over the sample period between 2007 and 2017. Our results showed that the extremely varied unemployment rates across the regions confirm that the persistent unemployment rate is the result not only of an excess labor supply, but also of a lack of coordination between the supply and demand. The results also indicated a remarkable decrease in the matching score over the period 2007-2017 for the 24 Tunisian regions.

Keywords: Unemployment, Coordination Failures, Matching Process, Beveridge Curve, Stochastic Frontier Ananlysis.

JEL Classification: E24, J20, J21, J64.

1. Introduction

The Tunisian labour market suffers from high and persistent unemployment which mainly affects young people, women and graduates. This unemployment differs greatly between regions, with rates of registered jobseekers varying in 2017 from 9.7% in the governorate of Ariana to 50.9% in the governorate of Tataouine; a ratio of one to five times. These territorial disparities in job applications also persist over time.

This situation reflects a series of disequilibria: a disequilibrium between the total supply and demand for labor, especially between the supply of and demand for skilled labour; a disequilibrium between the employment of men and women; and a structural disequilibrium between the available skills and those demanded by companies and necessary for the country's development. In fact, this mismatch of qualifications means that, despite the excessive unemployment of graduates, firms have difficulties in finding qualified profiles that meet their expectations besides; there is a structural problem of matching and communication between the training and education system that produces qualifications, on the one hand, and the firms in demand for qualified labour, on the other.

The disequilibrium is above all global and linked to various factors of labour supply and demand. The demographic factor is the main factor on the supply side. Despite the slowdown of population growth since the mid-1990s, the labour force continues to increase and the pressure on the labour market is set to persist. This pressure is the result of several factors. Firstly, there has been an explosion in the number of young graduates, especially from higher education, and a change in the structure of the working population. The most remarkable aspect of the evolution of the population concerns the number of students and

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graduates of Tunisian universities, which tripled in 15 years (between 1995 and 2010) and the place of young women. Moreover, the low growth of labour demand and the structure of employment and job vacancies are the main indicators of the disequilibrium in demand.

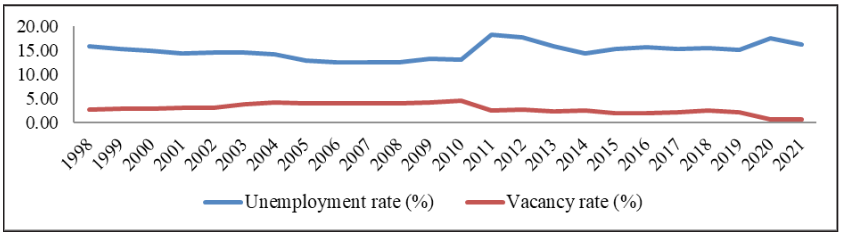

Figure 1. *Unempoyment and vacancy rates in Tunisia (1998-2021)* **Source:** *National Institute of Statistics in Tunisia; authors' calculations following El Bekri (2003).*

Figure 1 shows the unemployment rate and the job vacancy rate from 1998 to 2021. Over the period 1989 to 2010, both series moved towards each other, diverging rapidly as the economy entered a recession. For the first time, the unemployment rate crossed the 18% mark in 2011 due to the political instability (revolution) in Tunisia, raising concerns about the overall health of the labour market due to inefficiencies in the job-matching process. In addition, Tunisia, like many other countries, was forced to close its economy due to the COVID-19 pandemic. This resulted in the largest increase in unemployment that Tunisia has seen in the last decade. The unemployment rate rose to 17.4% in 2020, while the job vacancy rate dropped sharply during this period to 0.68%.

In the literature, several empirical analyses, such as those of Blanchard and Diamond (1989), Sarides (1986), Layard et al. (1991, 1996) was put forward, which consist in estimating the matching function of the aggregate data where the variables are structured in time series but ignored the regional disparities. Another line of research, such as that of Cole and Smith (1996), Anderson and Burgess (2000), Kangasharju et al. (2005), Hynnienen (2005), Kano and Ohta (2005) has shown how matching inefficiencies and regional disparities in structural factors contribute to regional and aggregate unemployment. They considered that the specification with regional data was very interesting because it controls such observable heterogeneity between the regions and corrects the aggregation error.

Because the matching process is comparable to the production on, our main objective in this work is to estimate the matching efficiency of the Tunisian regional labour market, using the the stochastic frontier method.

Therefore, this paper is structured as follows. Section 2 focuses on the theoretical and empirical literature on the relationship between unemployment and the coordination failure. In section 3, we present the econometric methodology and the obtained results. Finally, section 4 summarizes the findings and concludes the paper.

2. Literature Review

2.1 Theoretical Framework

On the other hand, a plausible source of coordination failure in the labor market is the matching process by which available jobs and suitable workers are brought together. This is a process that requires firms to spend resources and time finding and hiring workers and unemployed workers to spend time and effort finding suitable jobs. However, the possibility of coordination failure occurs because firms' hiring decisions and workers' job search efforts are complements (Rocheteau and Tasci, 2007).

According to the matching theory, the reason unemployment persists is that the process of matching labor supply and demand is failing because it is slow and expensive. Thus, even in times of high economic activity, workers may not quickly find work because information never perfectly flows and the offered jobs never perfectly match the labor supply. As a result of these failures, there will always be workers who do not find jobs and also companies that have vacancies. In practice, this coexistence of unfilled jobs and unemployed workers is represented by a matching function determining the number of hires made from the job offers and job demands.

In fact, the matching function is firmly connected to the Beveridge curve. The curve was first described by William Beveridge in 1958 and has been widely discussed in the economics literature and found its most famous application in the search and matching model of Diamond et al.(1994). The Beveridge curve is a graphical representation of the matching process that describes the relationship between the vacancy rate and the unemployment rate in equilibrium, where the number of vacancies, which is a proportion of the labour force, is generally negative (decreasing) and convex at the origin, which supports the global matching function (Pissarides, 2011). Therefore, if the curve shifts to the right and upwards, most researchers conclude that the employers post more job offers but do not like what they see among potential new employees.

However, Beveridge curves significantly differ from one country to another and also change over time. Theoretically, despite downward sloping, some Beveridge curves take on a variety of shapes, implying that economies exhibit very heterogeneous levels of mismatch. For example, some countries manage to quickly reduce mismatches after an economic downturn, while others do not.

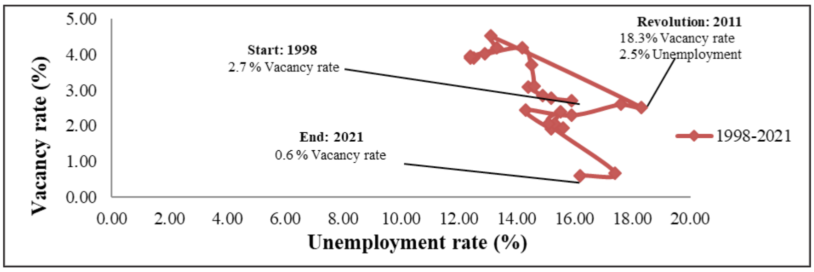

Figure 2. *Beveridge Curve in Tunisia (1998-2021)* **Source**: *National Institute of Statistics in Tunisia ; authors' calculations following El Bekri (2003).*

Moreover, the Beveridge curve, as illustrated in Figure 2, suggests that the Tunisian labor market is in mismatch especially during the period 2003-2010. As a result, the curve moves away from the origin (the initial year 1998) and seems to establish a new Beveridge curve upwards and to the left. This means that the rate of job creation was increasing and the unemployment rate was decreasing. In other words, the skills required by employers do not match the skills of the job seekers. This suggests that the Tunisian labor market is less efficient in the process of matching jobs and workers during this period.

In fact, from the beginning of the 2011 revolution until the end of 2013, the curve shifted lower and further to the right as the rate of job creation declined and the unemployment rate increased. Then, the outward shift of the Beveridge curve can be explained as follows. Frstly, by the dismissal of workers in all sectors and the closure of businesses throughout the country due to the political instability that Tunisia experienced in 2011. Secondly, by a mismatch between available jobs and the unemployed, in terms of skills or localization, or by employers' delay in hiring unemployed due to economic uncertainty.

Moreover, since the start of the Covid-19 pandemic, there has been a noticeable decline in job creation. Therefore, in times of recession, when unemployment is high, there are usually fewer jobs opened, which reduces unemployment. Indeed, it is clear that one of the key challenges for economic policy in the coming years is to ensure that the curve does not shift to the right again, as it did in 2011.

2.2 Empirical Studies

In the empirical literature, a large number of studies conducted by different methods and data sets give a surprisingly unanimous opinion in favour of the global matching function. In this vein, Petrongolo and Pissarides (2001) listed three different types of studies from which evidence about the global matching function has been accumulated. On the other hand, studies considering the joint movement of both the vacancy and unemployment rates, which is known as Beveridge, and estimates of the aggregate matching function with national and regional data and the study of the transition probabilities of individuals from unemployment to employment.

Ibourk and Perelman (2001) estimated efficiency frontier methods using two parametric and non-parametric approaches of a stochastic and deterministic nature, respectively for the evaluation of the matching processes in the Moroccan graduate labor market during the period 1995M01-1997M12. The results showed that there is an agreement between the different used estimation methods, including the fixed effects method generally used in the literature. They also found that the hypothesis of increasing returns to scale should be retained, confirming the fact that it is in large markets that the supply and demand matches are most likely to succeed.

Kano and Ohta (2002) showed the matching function using annual panel data covering 47 Japanese prefectures from 1972 to 1999, which allows for the variation in matching efficiency across regions. They also found that the matching function has decreasing returns to scale.

El Bekri (2003) proposed an analysis of the evolution of the skilled labor market in Tunisia over the period 1980-1998. Based on the annual stocks of registered jobs and the annual stocks of vacancies reported by firms as well as on the annual flows of placements made by the Tunisian Employment Agency (TEA), the author estimated a matching function and highlighted the increased efficiency of the skilled labor matching process over the period 1980-1998.

Destefanis and Fonseca (2004) considered the unemployment-vacancy relationship in Italian regions and estimated it as a production frontier. They relied on the labor market data in four main territorial areas (Northwest, Northeast, the Center and Mezzogiorno) throughout 1992 Q4-2003 Q4. Thus, the obtained results give broadly favorable evidence for the existence of a Beveridge curve in the 1990s in the main territorial areas. Therefore, huge differences in efficiency are evident between the Mezzogiorno and the rest of the country.

Fahr and Sunde (2005) examined the efficiency of the matching process between the job seekers and the vacancies for the years 1980 to 1997 for 117 regions in West Germany, using variation across the market regions and over time. Then, the results of a stochastic frontier analysis shed new light on regional differences in the search frictions and on the consequences of German reunification on the matching process. This study also provided new evidence on the complex interactions between the spatial contingencies of regional labor markets. In this way, matching efficiency decreases with a spatial autocorrelation in hiring, implying indirect evidence of crowding externalities.

Lahtonen (2006) analyzed an empirical matching function that accounts for the differences in the educational background of the job seekers. In fact, the used monthly data include 173 Finland labor offices and cover the years 1991 to 2002. The results revealed that an increase of the relative number of primary or highly skilled job seekers increases the ability of the labor market to form new matches while the corresponding effect of job seekers with secondary education is negative. In addition, the long-term unemployed, under 25 and over 50, have a negative effect on monthly matches.

Hynninen (2009) examined the technical efficiency of Finland's labor market matching using a stochastic frontier approach. The used dataset consists of monthly data from 145 local labor offices in Finland during the period 1995M01-2004M09. According to the obtained results, there are notable differences in matching efficiency between regions, which may significantly contribute to the number of filled vacancies. Therefore, if all regions were as efficient as the most efficient ones, the number of total matches per month would increase by over 10%, whereas if inefficiency had no role in the matching function, the number of matches would increase by almost 24%. Moreover, inactive and highly skilled job seekers improve the technical efficiency of the matching function.

Bou Abid and Drine (2011) studied the stochastic frontier approach and estimated, for the first time, the matching function for Tunisia using disaggregated data, based on annual data for 23 regional labor offices over the period 1984-2004. In fact, they included additional variables as determinants of matching efficiency and regional disparities. The obtained results showed that the extremely different levels of unemployment across regions and the deep changes in the job creation process support the view that the persistently high unemployment rate is the result not only of an excess labor supply, but also of a deficit between the supply and demand (sector, location, and skills).

Lin and Miyamoto (2012) examined the search and match model to describe the overall dynamics of the Japanese labor market during 1980Q1-2009Q4 in a full information setting. They developed a model for Japanese unemployment and job vacancy data. They found that the model successfully matches the volatility of unemployment and job vacancies, but it does not match the volatility of the output and wages. Their results also showed that productivity and separation shocks contribute to the movements in unemployment and vacancies, while productivity shocks are more important.

Amara et al. (2013) analyzed the matching process that relates the number of completed placements to a given stock of vacancies and unemployed workers, using Tunisian regional data for 23 governorates over the period 1984-2008. More precisely, the authors used spatial econometric techniques on panel data to explicitly take into account spatial effects, including proximity interaction, spatial heterogeneity and individual and temporal effects. Their results showed that taking into account these effects generates decreasing returns to scale in the Tunisian labor market. The authors also showed that job seekers in the neighboring governorates cause an increasing difficulty in the matching process within the local market.

Antczak et al. (2016) demonstrated efficiency in a labor market matching process in Poland, applying a stochastic frontier method to the matching function models of NUTS-1 to NUTS-4 units for the period 2000-2014. Their results showed that the labor market heterogeneity in spatial and temporal perspectives and the determinants of matching inefficiency imply that different policy measures should be applied to improve the efficiency of the labor market matching process.

Pater (2017) applied a multivariate unobserved component model and a Bayesian vector autoregression (BVAR) model and data from the U.S. economy during 1955Q1-2016Q1. His empirical analysis showed that the vacancy and unemployment rates have two components. The first is the effect of an aggregate labor demand shock, which has transient negative effects on job vacancies and unemployment. This results in a traditional negatively sloped Beveridge curve. The second shock, which is derived from the disruption of the unemployed, causes permanent changes in the direction of the unemployment and the vacancy rates. Moreover, it explains the changes in the negatively sloped Beveridge curve, especially in the long run.

Koubaa (2017) examined the matching process for Tunisia using disaggregated data for 23 regions over the period 1984-2004. In fact, using Panel Smooth Transition Regression (PSTR) models, she assumed that the rise of the unemployment rate is the result of regional disparities that produce variations in matching efficiency across regions. The obtained results indicated that the insertion of women, the share of qualification and the population density significantly contribute to explain the asymmetry of the matching process between regions. She concluded that hiring in Tunisia is essentially driven by the stock of vacancies in the region. However, the willingness of job seekers obviously remains low although it differs across regions and appears to be relatively high in urban regions.

Holmes and Otero (2020) provided an initial analysis of the Beveridge curve relationship conducted using a state-level pairwise approach.They used seasonally adjusted monthly data on the unemployment and vacancy rates for 48 U.S. states over the sample period between 2005m5 and 2018m7. Their results initially confirmed the existence of negatively sloped pairwise Beveridge curves across the U.S. States. In fact, they found that significant factors in matching efficiency include not only inter-state distance, but also labor force participation, home ownership, and relative housing affordability. They provided additional support for the idea that increased advertising of construction vacancies can significantly contribute to job matching.

Crawley et al. (2021) analyzed monthly U.S. labor market data and estimated matching efficiency rates using different measures of unemployment, namely the MGARCH model for the period 1994-2018. They found that labor market dynamics after the global financial crisis are correlated with a lower growth rate of matching efficiency between the unemployed and the jobs. In particular, the inclusion of part-time workers for economic reasons, capturing levels of underemployment, allows for frictions in the job-matching process to be taken into account to better describe the labor market dynamics observed throughout the last expansion period. Their results suggest that changes in alternative measures of labor underutilization are more important than they were in explaining the employment dynamics.

2. 3. Econometric Methodology and Results

2. 3.1 Specification of the Stochastic Frontier Matching Model

The stochastic frontier model, which was originally developed by Aigner et al. (1977) and Meeusen and Van Den Broeck (1977), has a significant contribution to the econometric modeling of the cost (or production) function and to the estimation of the technical inefficiency of firms. The analysis of the stochastic frontiers started with cross-sectional work then, another work emerged under the name of panel data (Lee and Schmidt (1993); Cornel et al. (1990) and Greene (2005a)). In our work, we will rely on panel data models because the matching process is comparable to a production process and our main objective in this work is to estimate the matching efficiency of the Tunisian labor market, Moreover, the method we chose is naturally the stochastic frontier method.Therefore, the matching process is usually determined by the familiar Cobb-Douglas production function (Pissarides 2000):

$$M_{i,t} = AS_{i,t-1}^{\alpha} V_{i,t-1}^{\beta} \qquad (1)$$

with $0 > \alpha <1$ et $0 > \beta <1$, where $M_{i,t}$, $S_{i,t-1}$ and $V_{i,t-1}$ denotes the placements made in year t, the stock of jobseekers and the stock of vacancies at the end of the previous year (t-1), respectively. The constant A shows the “mismatch parameter”, the “scale parameter” and the “efficiency parameter”, etc. α and β are parameters to be estimated, and have been analyzed in particular as measures of returns to scale (α + β)[1] in the matching process. Indeed, the standard

[1]Let α+β be used to estimate the nature of the returns to scale that conditions the dynamics of recruitment flows. This return increases if α+β>1; constant if α+β=1 and decreases if α+β<1.

theories are based on the hypothesis of constant returns (Pissarides, 2000), increasing returns (Anderson and Burgess, 2000, Boeri and Burda 1996, Van Ours, 1995) or decreasing returns (Hynninen et al., 2006 and Ohta, 2002). According to Weitzman (1982), and Aghion and Blanchard (1994), the ultimate source of equilibrium unemployment is increasing the returns to scale.

On the other hand, the stochastic logarithmic production frontier model assumes the following form, as developed by Battese and Coelli (1995) and Greene (2005a, b):

$$lnM_{i,t} = \left[\mu_i + \alpha lnS_{i,t-1} + \beta lnV_{i,t-1}\right] + v_{i,t} - u_{i,t} \quad (2)$$

The expression in square brackets, which indicates the matching frontier that gives the maximum output, can be obtained at given quantities of production inputs, job seekers and vacancies. Then, the observable error term $\varepsilon_{i,t} = v_{i,t} - u_{i,t}$ consists of directly unobservable components. It is therefore assumed that $v_{i,t}$ are independently and identically distributed random variables according to a normal distribution $N(0, \sigma_v^2)$. The second non-negative random term $u_{i,t}$ represents the matching inefficiency of region i in period t. The random variables are supposed to be independently distributed from $v_{i,t}$, according to the $N\left(Z_{j,it}\delta_j, \sigma_u^2\right)$ distribution truncated at zero (Coelli 1997). Where $Z_{j,it}$, is a vector of inefficiency regressors and δ_j are the coefficients to be estimated. . The variance of the composed error term is given by $\sigma^2 = \sigma_v^2 + \sigma_u^2$. Then, the relative importance of the residual correlated with the inefficiency term is $= \sigma_u^2/\sigma^2$. and σ^2 and γ are parameters to be estimated instead of σ_v^2 and σ_u^2 (Battese and Coelli, 1995). Moreover, with $0 < \gamma < 1$, γ represents the relative share of the variance explained by technical inefficiency. Therefore, with the stochastic approach in the selected model, the deviation from the maximum possible match may be due to the inefficiency of the job seekers or to random factors that occur during the matching process. As the value of γ is closer to 1, the more this deviation is attributed to the inefficiency of the actors, and thus the random effects are reduced (the model would then be deterministic). In fact, this indicator will play a key role in justifying the statistical consistency of the model.

An inefficiency term is distributed by "environmental factors" that change across regional units and over time. Thus, the inefficiency term is a function of these environmental factors, $u_{i,t} = Z_{j,it}\delta_j + w_{i,t}$, where the random variable $w_{i,t}$ is determined by the truncation of the normal distribution with mean zero and variance σ_u^2 such that the truncation point is $-Z_{j,it}\delta_j$, i.e., $w_{i.t} \geq -Z_{j,it}\delta_j$. These assumptions are consistent with $u_{i,t}$, being non-negative truncations of the distribution $N\left(Z_{j,it}\delta_j, \sigma_u^2\right)$ (Battese and Coelli 1995). This specification implies that all environmental factors that might increase or decrease production inefficiency directly affect the degree of technical efficiency but not the form of the production technology as in the classical fixed effects framework (Coelli et al., 1999).

Therefore, the parameters of the stochastic frontier and the efficiency term are simultaneously estimated by maximizing the log likelihood function of the model (Coelli 1997, Coelli et al., 1998). The conditional estimates of the efficiency coefficients $TE_{i,t}$ are calculated as:

$$TE_{i,t} = \left[exp\left(-u_{i,t}^*\right)|M, S, V, Z\right] \quad (3)$$

Then, the explanatory variables for inefficiency (in the form of the Z vector) in our model are as follows: the labor force (L), the population density (D) and the number of firms (F), while the efficiency measure, which is absolute, is not relative to the best in the sample. In fact, it is equal to 1 when the matches are on the frontier, otherwise $TE_{i,t} < 1$.

3.2 Data Description

The data we used in this work were collected from the National Institute of Statistics (INS) and the National Agency for Employment and Independent Work (ANETI) for each of the 24 Tunisian regions over a period of 11 years (from 2007 to 2017). The stock of unemployment is defined here as the number of job seekers at the end of the year t-1 (S_{t-1}), and the stock of vacancies as the number of job offers at the end of the year t-1 (V_{t-1}), then (M_t) are the placements made during year t.

The basic data for the matching model tells us that there are other variables that affect matching and theories suggest what these variables might be. These include variables describing the labor force (L) (see Pissarides, 1990 and Cadiou et al., 2002), the population density[2] (D), and the number of firms (F). With regard to the population density, Lahtonen (2006) found evidence which supports the hypothesis that densely populated areas are more productive in matching. As for Coles and Smith (1996), they presented this hypothesis by stating that densely populated areas require less effort

[2]Calculation made by the author using the formula: total population/area.

and cost to communicate, which results in more search activity. On the other hand, Kano and Ohta (2005) suggested that a higher population density is also related to a higher degree of heterogeneity, leading to increased search frictions. For their part, Wahba and Zenou (2005) considered the population density as an indicator of the size of social networks and thus of the speed of information transmission. They conclude that as long as the network remains of a reasonable size, its size has a positive effect on matching efficiency. However, the effect may become negative in very densely populated areas due to the dominant opposite congestion effect. Regarding the number of firms, Goerke (1997b) noted that it is difficult to determine whether the increase of employment is due to an increase of employment per firm and/or the existence of a larger number of firms. Moreover, the model presented by Sedlácek (2019) focuses on the entry of firms into a search and matching framework emphasizing the importance of general equilibrium retroaction effects operating via the frictional labor market that go beyond an endogenous wage response.

Table 1. *The evolution of unemplyment rate, vacancy rate and labor market tension in the Tunisian regions over the period 2007-2017.*

Regions	S/L 2007	S/L 2011	S/L 2017	V/L 2007	V/L 2011	V/L 2017	V/S 2007	V/S 2011	V/S 2017
Tunis	12.5	17.3	11.2	4.1	3.3	2.0	32.8	19.2	17.6
Ariana	9.9	13.9	9.7	2.4	2.7	1.2	23.9	19.3	12.4
Ben Arous	14.4	20.5	13.3	3.3	3.8	1.8	23.0	18.4	13.8
Mannouba	14.3	20.2	15.9	2.2	1.7	1.2	15.4	8.2	7.4
Nabeul	11.7	14.5	12.8	1.3	1.5	1.2	11.2	10.1	9.0
Zaghouan	23.6	19.2	24.6	23.4	13.3	14.8	99.3	69.3	60.0
Bizerte	17.7	16.7	17.6	7.3	2.2	2.7	40.9	12.9	15.6
Beja	12.5	23.2	18.9	1.3	1.7	1.1	10.7	7.2	5.7
Jendouba	17.0	26.4	24.9	4.3	1.5	1.9	25.6	5.7	7.7
Kef	16.0	21.3	21.2	2.9	1.9	1.2	18.1	9.1	5.6
Siliana	21.2	23.9	21.4	3.2	2.0	1.8	14.8	8.4	8.2
Sousse	14.2	18.4	14.0	7.5	5.2	3.4	52.8	28.0	24.4
Monastir	14.4	21.9	14.9	6.7	4.4	2.5	46.9	19.9	16.7
Mahdia	11.2	20.0	12.3	3.0	2.5	1.7	26.8	12.4	13.8
Sfax	12.3	16.3	13.0	4.7	1.8	1.8	38.5	11.0	14.0
Kairouan	14.0	17.2	17.1	1.9	0.3	0.9	13.7	1.7	5.0
Kasserine	16.1	26.0	22.7	2.6	4.0	1.6	16.3	15.5	7.2
Sidi Bouzid	13.4	22.3	24.5	1.8	0.8	0.8	13.6	3.6	3.1
Gabes	18.7	35.8	32.1	3.8	1.3	0.7	20.4	3.7	2.1
Medenine	15.7	26.9	22.4	2.1	1.0	1.0	13.5	3.8	4.4
Tataouine	24.0	56.8	50.9	1.7	0.8	1.1	7.1	1.4	2.1
Gafsa	27.2	45.0	37.1	2.7	2.5	1.9	9.9	5.6	5.1
Tozeur	26.3	41.4	31.4	7.8	3.6	4.3	29.8	8.7	13.8
Kebili	23.7	40.6	28.3	3.5	4.9	1.9	14.7	12.0	6.7
Average	14.8	20.9	17.3	4.0	2.6	1.9	27.2	12.5	11.2

Source: *Author's calculation based on INS data ; S = unemployment stock; V = Vacancy stock; L = labor force; S/L and V/L are thus unemployment and vacancies rates, respectively, and V/S denotes tension in the labor market.*

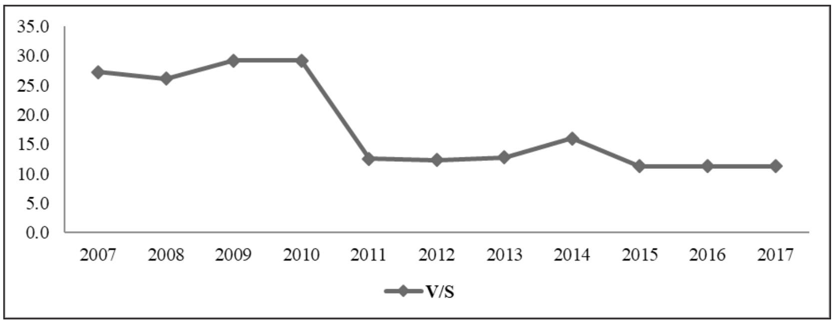

Figure 3. *Evolution of the labor market tension in Tunisia over the period 2007-2017.* **Source**: *Author's calculation based on INS data ; V/S denotes tension in the labor market*

Figure 3 also tracks the evolution of the labor market tension in Tunisia. At the national level, there has been a remarkable decrease from 27.2 to 11.2 during the period 2007-2017. This deterioration is the consequence of insufficient job creation and increasing unemployment. In addition to the crisis, the 2011 revolution is partly responsible for the slackening of the labor market in Tunisia.

Figure 4 examines the probability of matching and hiring at the national level between 2007 and 2017. There was a downward trend in the probability of matching during the 2007-2011 period. This decline accounts for the hiring difficulties faced by firms, i.e., firms are finding it more difficult to fill their vacancies. However, since 2012, there has been a slight increase of this probability, which stabilized at 70% level in 2017. Among the regions with the most moderate matching difficulties, we find quite logically that Tataouine is one of the regions where the potential workforce is largely under-employed.

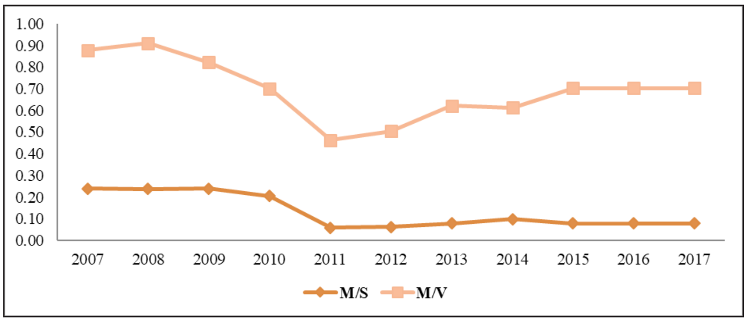

Figure 4. *The probabilities of matching and hiring an unemployed person in Tunisia over the 2007-2017 period* **Source:** *Author's calculation based on INS data; M= Placement made; M/S= Probability of hiring an unemployed person, i.e., the probability of moving from unemployment to employment; and M/V= Probability of matching, i.e., the probability of filling a job vacancy.*

The unemployed hiring probability captures the difficulties that the unemployed face in finding a job. At the national level, out of every 100 unemployed people registered with the ANETI, only 8 unemployed could find jobs during 2017.

Table 2. *The probabilities of matching and hiring an unemployed person in the Tunisian regions over the period 2007-2017*

Régions	M/S 2007	M/S 2017	M/V 2007	M/V 2017
Tunis	0.24	0.16	0.74	0.88
Ariana	0.19	0.10	0.81	0.83
Ben Arous	0.20	0.10	0.87	0.75
Mannouba	0.15	0.4	0.96	0.56
Nabeul	0.09	0.05	0.84	0.56
Zaghouan	0.92	0.38	0.93	0.64
Bizerte	0.37	0.13	0.91	0.85
Beja	0.11	0.03	1.00	0.58
Jendouba	0.24	0.08	0.95	1.00
Kef	0.09	0.03	0.52	0.45
Siliana	0.15	0.08	1.00	1.00
Sousse	0.45	0.15	0.84	0.62
Monastir	0.38	0.12	0.81	0.71
Mahdia	0.25	0.12	0.92	0.84
Sfax	0.37	0.07	0.96	0.52
Kairouan	0.13	0.03	0.94	0.67
Kasserine	0.15	0.05	0.91	0.71
Sidi Bouzid	0.11	0.02	0.83	0.56
Gabes	0.18	0.02	0.88	1.00
Medenine	0.12	0.03	0.89	0.63
Tataouine	0.08	0.02	1.00	1.00
Gafsa	0.06	0.03	0.64	0.62
Tozeur	0.27	0.05	0.92	0.38
Kebili	0.13	0.04	0.87	0.60
Tunisie	0.24	0.08	0.88	0.70

Source: *Author's calculation based on INS data, M= Placement made; M/S= Probability of hiring an unemployed person, i.e., theprobability of moving from unemployment to employment; and M/V= Probability of matching, i.e., the probability of filling a job vacancy.*

According to Table 2, there are only 10 governorates where their hiring probabilities exceeded the national level. Among these regions are Zaghouan, Tunis, Bizerte and Sousse (coastal regions), for which the probabilities are respectively (0.38, 0.16, 0.13 and 0 .15 for the year 2017), while 14 governorates were below the national level. Most of these regions are located in the interior of the country (Beja, Sidi Bouzid, Gafsa and Tataouine) and have an unemployment rate much higher than the national average. This confirms the discrimination between the Tunisian regions since the independence.

In brief, the lower the number of vacancies (relative to the number of the unemployed) in a region, the more easily firms in that region can fill their vacancies, the less easily unemployed workers in that region can find jobs (e.g., Tataouine) and vice versa. In fact, this validates the theory of Pissarides' matching models.

In fact, table 3 summarizes the descriptive statistics of the multi-year data. On average, there are 28.250 registered job seekers and 4.783 job vacancies in a local office, which represents a recruitment level of approximately 3.404 employees. In addition, this variable has a standard deviation of (3.429), with a minimum of (0.1) and a maximum of (15.5). We also notice a high volatility of the variables D and F.

Table 3. *Descriptive statistics*

Variables	Units	Average==	Sta.dev	Min	Max	Observations
M	Thousands	3.404	3.429	0.1	15.5	264
S	Thousands	28.256	11.744	8.4	68.3	264
V	Thousands	4.783	4.283	0.3	20.2	264
L	Thousands	159.344	94.902	32	460	264
D	Inhabitant\km3	332.988	726.332	3.710	3727.778	264
F	Thousands	26.452	24.426	4.7	137.9	264

M= Placement made; S=Unemployment stock; V =Vacancy stock; L = Labor force; D= Population density; and F= Number of firms.

3. Results and Discussion

In this context, two conventional panel data models and three stochastic frontier models were estimated. The results of the estimations are reported in Table 4. The first two columns show the estimation results for the random and fixed effects models. The estimation results for both models show that the coefficients correlated with the job demand (S) and job supply (V) are statistically significant (their respective p-values < 5%). However, the effect of job demand on placements made seems negative. As concluded by Amara et al. (2013), this provides an explanation for the inability of the labor market policies to absorb the large numbers of job seekers.

For the random effects model (estimation is done by GCMs), the Wald statistics is used to test the joint significance of the parameters. Thus, the Wald statistics gives a value of 937.85 with a probability of 0.000 (<5%), which strongly rejects the null hypothesis of the presence of random effects. Thus, the $R^2_{Between}$, which informs on the importance of the random effects in the model is equal to 89.2%, while the R^2_{Within} indicates the importance of the inter-individual variability (individual effects) of the dependent variable explained by that of the explanatory variables at a rate of 75.1%. In all cases, the $R^2_{Overall}$ provides information on the overall robustness of the adjustment (or model).

In addition, the Fischer statistics for the fixed-effects model (estimation is done by OLS): $F(5,235) = 148.19$ confirms the heterogeneity of individuals as a fixed effect, since the p-value < 5%. Indeed, in the fixed-effects model, the R^2_{Within} is the most appropriate because it gives the share of the within-individual variability (time effects) of the dependent variable explained by that of the explanatory variables. The value of R^2_{Within} (75.9%) is higher than that of $R^2_{Between}$ (7.3%). In this case, and according to Cameron and Trivedi (2009), the fixed effects model is appropriate for these data. In all cases, the $R^2_{Overall}$ provides information on the overall robustness of the adjustment (or model). According to the Hausman test, the probability of the chi2 is equal to 0.000, so, we can conclude that the estimators of the random effects model are biased. It is therefore preferable to use those of the fixed effects model.

The three stochastic frontier models are represented in the third, fourth and fifth columns. The third column presents the estimation results from the time-varying fixed-effects model of Lee and Schmidt (1993). The fourth column contains the results from the time-invariant fixed effects model of Cornel, Schmidt, and Sickles (1990), while the fifth column contains the results from the true fixed effects model of Greene (2005a).

Table 4. *Estimation Results*[a]

Variables	Conventional panel data models		Stochastic frontier models		
Dependent variable: $\ln M_t$	Random effects	Fixed effects	Lee and Schmidt (1993)	Cornwel, Schmidt and Sickles (1990)	Greene (2005a)
Constant	0.371 (0.480)	5.705 (0.059)	-	-	-
$\ln S_{t-1}$	-0.844 (0.000)	-0.967 (0.000)	-0.550(0.144)	-0.927 (0.000)	-0.698 (0.000)
$\ln V_{t-1}$	1.003 (0.000)	0.970 (0.000)	0.903 (0.000)	0.934 (0.000)	0.955 (0.000)
$\ln L_{t-1}$	0.310 (0.093)	-0.001 (0.995)	-0.435(0.525)	-0.079 (0.764)	-0.081 (0.000)
$\ln D_{t-1}$	-0.046 (0.480)	-0.929 (0.266)	-0.346 (0.821)	3.787 (0.065)	-0.436 (0.000)
$\ln F_{t-1}$	0.218 (0.191)	0.462 (0.106)	0.510(0.648)	1.446 (0.114)	-0.289 (0.000)
Returns to scale ($\alpha + \beta$)	0.159 (0.000)	0.003 (0.000)	0.353 (0.247)	0.007 (0.985)	0.257 (0.000)
R^2_{Within}	0.7517	0.7592	-	-	-
$R^2_{Between}$	0.8922	0.0734	-	-	-
$R^2_{Overall}$	0.8507	0.0000	-	-	
F(5, 235)	-	148.19 (0.000)	-	-	-
Wald chi2(5)	937.85 (0.000)	-	-	-	-
Husman test (khi2)	-	100.12 (0.000)	-	-	-
Sigma carré (σ^2)	-	-	0.564	39.752	3.877
Gamma (γ)	-	-	0.893	0.998	0.019
Observations	264	264	264	264	264

[a] is the probability in parentheses. σ^2 is the sum of variances of the stochastic error and the inefficiency tem and γ is the ratio of variance of the inefficiency term over the total variance.

The results also suggested that the coefficients of the matching function are significant for both models (Cornel, Schmidt, and Sickles (1990) and Greene (2005a)). Indeed, the coefficients correlated with the log of the number of the unemployed and job vacancies give the estimated value of the elasticity of hiring with regard to these two variables on average over the entire sample. In other words, the placements made appear to be motivated more by the stock of vacancies and the stock of job seekers having a limited effect. In this sense, Bou Abid and Drine (2011) showed that the existence of an informal market operating in Tunisia and the fact that only jobseekers registered in employment offices are taken into account in the unemployment figures may lead to an underestimation of the α parameter. The values of α and β from the estimation of a true fixed effects model (Greene, 2005a) are -0.698 and 0.956, respectively. A similar result was obtained by Broersma and Van Ours (1999) (α = -0.1 and β = 0.9) for the Dutch case, Ibourk and Perelman (2001) (α= 0.18 and β = 0.81) for the Moroccan labor market case, and Burgess and Profit (2001) (α = 0.003 and β = 0.4) for the United Kingdom's case. The rather low value of α reflects a difference in measurement between this study and those of Kano and Ohta (2005) (α = 0.6 and β = 0.3) for the case of Japan and Mumford and Smith (1999) (α = 0.9 and β = 0.1) for the case of Australia, especially with the existence of an informal labor market operating in Tunisia. In fact, the informal sector represented 44.8% of jobs in Tunisia in 2019 according to the National Institute of Statistics. This can be explained by the lack of sufficient orientation, accompaniment and support in the search for a job by the public employment service and the National Agency for Employment and Self-Employment (ANETI), making it difficult to access ordinary employment in companies.

Moreover, the results in this table show that there is a decreasing return to scale (α+β<1 =0.25) for the different specifications and that the Tunisian labor market is highly dependent on the stock of vacancies (it is significant at 0.1% level in the Greene model). This implies tat there is a negative or zero impact of density (large market) on the efficiency of the matching process in the Tunisian labor market. Therefore, this result contradicts the prediction of Blanchard and Diamond (1989) that we should expect increasing returns to scale in denser and more fluid urban labor markets.

On the other hand, the findings of Lee Schmidt (1993), Cornel, Schmidt, and Sickles (1990), and Greene (2005a) models suggested that the inefficiency the component is the coefficient correlated with gamma (γ). Compared to the first two models, the true fixed effects model of Greene (2005a) yields the lowest coefficients (0.01). Indeed, if Gamma is close to 1, it straightforward shows that the large variation is explained by technical inefficiency in the stochastic frontier model, whereas if is close to zero, it simply means that a small variation is accounted for by technical inefficiency. Thus, it would be reasonable to estimate the stochastic frontier because the large variation would be simple and would come from random variation.

We can also observe that the coefficients correlated ciated with the different sources of friction in the Tunisian labor market are all significant for the true fixed effects model. However, the labor force (L_{t-1}) negatively and significantly affects the matching process. That is, a 1% increase of the labor force decreases the matching efficiency by 0.08%. Therefore, the demographic evolution and more precisely the growth of the labor force, as predicted by the neoclassical growth model, reduce the capital-to-labor ratio, which increases the interest rates and reduces the wages. In a frictional market, the agents reduce their job search efforts, which results in an increase of unemployment (Cadiou et al., 2002). Therefore, this consistent with the results observed by Pissarides (1990).

Then, the effect of the population density (D_{t-1}) on the matching efficiency is significantly negative. In other words, a 1% increase of the population density decreases the matching productivity by 0.43%. According to Wahba and Zenou (2005), this negative effect can be explained by the dominant opposite congestion effect. In other words, denser zones create negative externalities towards one another, because job seekers are in competition. Therefore, this result is in favor to Kano and Ohta's (2005) hypothesis that the region characterized by a more dispersed distribution of firms' hiring norms and workers' skill levels would show lower matching efficiency. This is because of a greater possibility of conflicts between the two parties' requirements, as hiring norms and skill levels should show a greater dispersion in more urbanized regions. This result also contradicts the claims of Coles and Smith (1996) and Lahtonen (2006) that densely populated areas are more productive in matching.

Contrary to what was expected, the number of firms (Ft-1) has a significant and negative effect on the matching efficiency. This can be explained by the inability of firms to hire more workers. In this sense, Goerke (1997b) pointed out that it is difficult to determine matching by the firm's growth.

Moreover, the estimation of the matching efficiency is studied along several dimensions. Regional differences are typically studied (e.g., Ilmakunnas and Pesola, 2003, Hynninen et al., 2009, Ibourk et al., 2004, and Bou abid and Drine, 2011), where most studies looked at changes in efficiency over time.

Table 5 illustrates the matching efficiency estimated in different regions based on the Greene (2005a) model. We chose the efficiency estimates from true fixed-effects model because all the variables are significant. On the other hand, the efficiency measures estimated for all regions range from a low level of 0.27 to a high of 0.97, with a mean of 0.81. Our results are therefore consistent with those reported in the existing literature on the matching efficiency. Over the period 2007-2017, the efficiency level ranged from 0.27 to 0.97, with a standard deviation of about 0.17. However, among the 24 regions, only 14 stand out with a higher level of efficiency than the national level and more than half of the governorates have unemployment rates higher than the national average (17.3%). It is therefore important to revise the guidelines for investment in human capital by studying the specific characteristics of job seekers in the regions (Boubakri, 2010).

Table 5. *Matching efficiency results per region*

Regions	Average	Sta.dev	Unemployment rate (%)	Regions	Average	Sta.dev	Unemployment rate (%)
Tunis	0.94	0.007	11.2	Monastir	0.89	0.013	14.9
Ariana	0.90	0.013	9.7	Mahdia	0.78	0.026	12.3
Ben Arous	0.85	0.019	13.3	Sfax	0.93	0.009	13.0
Mannouba	0.73	0.030	15.9	Kairouan	0.85	0.018	17.1
Nabeul	0.70	0.033	12.8	Kasserine	0.80	0.023	22.7
Zaghouan	0.89	0.013	24.6	Sidi Bouzid	0.66	0.036	24.5
Bizerte	0.94	0.007	17.6	Gabes	0.94	0.008	32.1
Béja	0.81	0.022	18.9	Medenine	0.88	0.014	22.4
Jendouba	0.97	0.004	24.9	Tataouine	0.95	0.007	50.9
Kef	0.55	0.044	21.2	Gafsa	0.93	0.009	37.1
Siliana	0.96	0.006	21.4	Tozeur	0.27	0.047	31.4
Sousse	0.76	0.028	14.0	Kebili	0.52	0.046	28.3
Average					0.81	0.16	17.3

As shown in Figure 5, there was a remarkable decrease of the matching score over the 2007/2017 period. This decrease calls into question the different efforts implemented by the Tunisian authority to improve the labor market performance. Therefore, our results are consistent with those found by Ibourk et al (2001) for the case of France but contradict the results found by Ilmakunnas and Pesola, 2003 for the case of Finland.

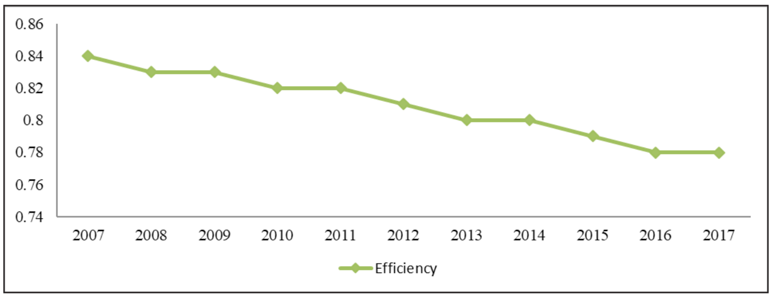

Figure 5. *The evolution of average matching efficiency over the period 2007-2017*

Indeed, the matching efficiency already began to decline before the 2011 recession. In fact, during the recession years, efficiency deteriorated further for all governorates. This decline in matching efficiency coincides with the growth of unemployment explains why unemployment appears to have a negative impact on efficiency. The deterioration of which may also reflect that the increase of the number of the unemployed is due to the coordination failures between the labor supply and demand. This suggests not only the existence of a considerable lack of information about the access to new job openings, but also a mismatch between the demanded ‑ skills and the qualities of the job-seekers. Therefore, the mismatch between the skills of young graduates and the needs of companies and the economy is a problem faced by training institutions. In fact, the solution to improve the employability of graduates lies in training structures that can identify the needs (current and future) and adapt their teaching to them.

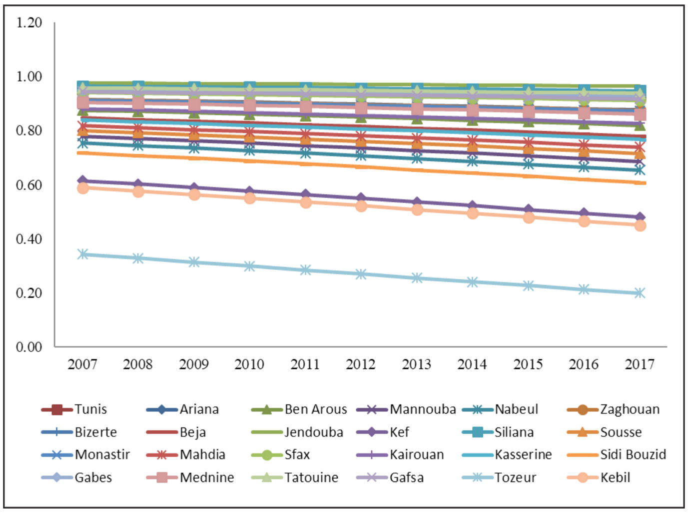

Figure 6. *The evolution of matching efficiency over the period 2007-2017 for 24 regions*

As shown in Figure 6, four main results can be identified. First, the matching efficiency for the regions (Jendouba, Siliana, Gabes, Gafsa and Tataouine) seems to be the most efficient with average scores of 0.97, 0.96, 0.94, 0.93 and 0.95, respectively. These regions also suffer from very high unemployment rates compared to the national level (17.3%) with respectively 24.9%, 21.4%, 32.1%, 37.1% and 50.9%). This result may reflect an increased use of job centers to find jobs and workers in high unemployment regions. It is also clear that low vacancy rates in these regions contribute to efficiency. In this sense, Bunders (2003) found that the regions with high unemployment rates generally have a higher matching efficiency than those with lower unemployment rates. Therefore, it can be argued that the high unemployment rate in these regions can be explained by the excess of job demand over supply. As pointed out by Fahr and Sunde (2002,), it is very important to understand the nature of the regional unemployment problem in order to design policies to alleviate it.

Second, unemployment was concentrated in the regions where the matching efficiency was the lowest. These regions are Tozeur, Kebili, Kef and Sidi Bouzid (0.27, 0.52, 0.55 and 0.66). The relatively high unemployment rates in these regions (31.4%, 28.3%, 21.2% and 24.5%) are explained by the mismatch between the job seekers and job vacancies. The mismatch of the offered and demanded skills has played a major role in the deterioration of the efficiency of the matching process. More precisely, the labor market regulation policies in these regions may be inefficient. In fact, in these circumstances, policy should focus more on reducing these inefficiencies.

Third, the regions of Tunis, Ariana and Sfax benefited from an efficient matching process (0.94, 0.90, 0.93) and low unemployment rates (11.2%, 9.7%, 13%). In fact, the regions of Tunis and Sfax are respectively the political and the industrial capital of the country. The concentration of companies and the quality of job seekers in these regions explain both the efficiency of the matching process and the low level of unemployment compared to the national level.

Fourth, some regions with low unemployment rates have relatively high vacancy rates, which may explain their low efficiency scores. These regions are coastal ones, such as Nabeul, Sousse and Mahdia). The low unemployment rate is probably explained by the efficiency of the tourism sector, which has managed to fill the demand for employment. However, the inefficiency of the matching process in these regions reflects the inability of the employment offices to disseminate information to job seekers and the mismatch between the required skills and the qualities of job seekers.

In fact, unemployment disparities are generally interpreted as the result of limited interregional labor mobility or differences in underlying regional labor market factors. Take, for example, the region of Gafsa, which suffers from an unemployment rate of 37.1% despite being a mining region and rich in natural resources, and the region of Ariana with a rate of 9.7%, which proves the regional discrimination and marginalization policy of the government since the independence.

In most research models, says Diamond (1982), it is suggested that spatial dispersion of units creates more friction and therefore more unemployment. According to Jackman and Roper (1989), L'Horty (1997) and Sneessens et al. (2002), regional mismatches are analyzed as a first explanation for the inefficiency of matching. In our case**,** Tunisia is very poorly ranked and the labor market suffers from structural problems. According to the Global Competitiveness Report 2014-2015, Tunisia's rank in terms of cooperation in labor-employer relations is 118[3].

[3]See WEF, The Global Competitiveness Report 2015.

4. Conclusion

To conclude, we can say that Tunisia has suffered for decades from high a unemployment and remarkable regional disparities despite multiple reforms and employment policies. This prompted us to adopt a regional labor market analysis to understand the role of regional disparities in the still high unemployment rate through a matching process. Again, we performed a stochastic frontier analysis for a period covering 2007 - 2017. The extremely varied unemployment rates across regions and the profound changes in the job creation process confirm that the persistently high unemployment rate is the result not only of excess labor supply, but also of a coordination failure between the supply and demand. Moreover, the market system suffers from a lack of coordination of the plans of firms and the unemployed who are desired by both, as the hiring decisions of firms and the job-seeking efforts of workers are complements. However, without corrective measures, the economy may remain stuck in states of underemployment. Therefore, the main focus should be on policy measures that the government can take to remedy unemployment.

Moreover, noticible differences in matching efficiency across regions were found, to have significant effects on the number of filled vacancies. There was also a remarkable decrease of the matching score over the 2007-2017 period,. which seems in contradiction with the results found by Ilmakunnas and Pesola (2003) whose matching efficiency increases over time.

However, there are limitations to the efficiency approach discussed in this article as it ignores the quality aspect of matches and focuses only on the number of matches. The fastest job offers are filled and the fastest job seekers find the best jobs. In fact, this may not be optimal. Therefore, taking the first acceptable offer may not be desirable if there is a decent chance that a better offer will arrive soon.

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