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SECTORAL SHIFTS, DIVERSIFICATION, REGIONAL UNEMPLOYMENT ON THE EVE OF REVOLUTION IN TUNISIA: A SEQUENTIAL SPATIALPANELAPPROACH

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Abstract

This paper investigates how sectoral shifts and industry specialization patterns have influenced Tunisian labor market performance in the recent past years. Building on a sequential spatial framework, while taking into account spatial dependencies and externalities, our empirical investigation highlights that sectoral shifts and congestion effects induced by labor-supply growth exert a negative impact on unemployment dynamics. Our results suggest that some Marshallian externalities manage to soften, and even reverse, the diversification induced effect on unemployment. Moreover, we report high spatial dependence, which evidences a higher degree of contagion. Additionally, negative spillovers of sectoral shifts contrast with positive spillovers of specialization pattern, initial unemployment rate, labor-supply growth and the excess labor demand growth rate. Finally, the revolution had a detrimental effect on unemployment growth, except in the center-west region where unemployment was an inevitable result of an inner-process.

JEL Classification: C23; L16; R23

Keywords: regional unemployment, sectoral shift, diversification, spatial dependence, spatial spillovers, transition, Tunisia

ملخص

تبحث هذه الورقة كيف أثرت التحولات القطاعية وأنماط صناعة التخصص على أداء سوق العمل التونسي في السنوات الماضية الأخيرة. بناء على متتابعة الإطار المكاني، ومع الأخذ بعين الاعتبار تبعيات المكانية والعوامل الخارجية، والتحقيق التجريبي لدينا نسلط الضوء في هذه الورقة على التحولات القطاعية وآثار الازدحام الناجمة عن نمو العمالة والإمدادات التي تمارس تأثيرا سلبيا على ديناميات البطالة. تشير نتائجنا إلى أن بعض العوامل الخارجية قد تلين، وحتى على العكس، مع أثر التنويع الناجم عن البطالة. وبالإضافة الى ذلك تتناقض الآثار غير المباشرة السلبية للتحولات القطاعية مع التداعيات الإيجابية لنمط التخصص، ومعدل البطالة الأولية، ونمو العمالة العرض ومعدل نمو الطلب على العمالة الزائدة. وأخيرا، كان للثورة تأثير ضار على نمو البطالة، ما عدا في منطقة وسط غرب حيث كانت نسبة البطالة نتيجة حتمية عملية-داخلية.

1. Introduction

Tunisia represents an interesting case study with its high degree of spatial heterogeneity in local labor market performance, ongoing economic upgrading process, increased disparities between -and within- regions, and the advent of the revolution (Jebili and Belkacem, 2015). Additionally, it is interesting to discuss the outcome of the presence of strongly specialized areas in Tunisia. The Portfolio hypothesis (Simon, 1988; Simon and Nardinelli, 1992) and Jacobs' theory (Jacobs, 1969) advocate that regions with a higher degree of diversification should better stand up to adverse shocks. In contrast, the Industrial Districts theory (Marshall, 1890; Becattini, 1990) suggests that due the presence of agglomeration economies, highly specialized areas should outperform the others.

The present paper is exploratory in nature and is not based on a deductive economic methodology; it is mainly concerned with the statistical analysis and forecast of the underlying economic indicators that characterize the functioning of regional labor markets, notably unemployment rate and growth rate. It aims to empirically assess the regional labor market impact of the revolution by taking into account the potential effects of the previous unemployment disparities between regions, the unemployment dynamics, the sectoral composition and some structural characteristics of the regional labor markets.

In order to set aside induced and genuine effects, we have adopted a sequential spatial approach, taking into account spatial dependencies and externalities. This approach conceptually meets the path analysis method. Besides, in order to track down the effects of aggregate disturbances, we have included a measure of industrial diversity - Gini index - along with the Lilien Index (Neumann and Topel, 1991; Chiarini and Piselli, 2000; Robson, 2009; Pastore et al., 2011).

Numerous studies have been dealt with the effect of sectoral shifts and industry specialization patterns on local labor market performance and, especially, local unemployment (Lilien, 1982 ; Samson, 1985; Neumann and Topel, 1991; Chiarini and Piselli, 2000 ; Krajnyak and Sommer, 2004; Newell and Pastore, 2006; Ferragina and Pastore, 2008; Robson, 2009; Pastore et al., 2011; among others). This study contributes to this literature by focusing on the local Tunisian labor market over the past recent years ($2004-11$) when huge structural changes occurred in the country. To this end, we develop a methodological framework that innovates with respect to the existent literature along several dimensions. First of all, the Tunisian case has never been studied before; then, we test for the presence of interregional spillovers and spatial contagion, which is quite a novelty in this literature. Furthermore, in the footsteps of Pastore et al. (2011), we propose to jointly model possible overlapping effects of Jacobsian and Marshallian economies.

As for the policy implications of this work, it should be noted that the regional level is particularly important both in terms of the revolution objectives, and also considering that, in the multilevel policy design in Tunisia, key labor market policies have to be decentralized at the sub-national level. We propose to investigate whether the bigger impact was on the most penalized or the previous best-performing regions and how the local industry mix and structural characteristics shaped the labor market performance and their response to the revolution.

The structure of the paper is as follows. Section 2 covers the main literature on the theories and empirical evidence about unemployment dynamics at the regional level. The vulnerability of the regional labor market in Tunisia to sectoral shifts is discussed in Section 3. Exploratory investigations are presented and commented on in Sections 4 and 5. Section 6 presents the econometric framework and our main empirical findings; taking into account the complex space-time components, we model and discuss the heterogeneity in regional labor markets. Section 7 concludes.

2. Literature Review

Among the structural determinants, the effect of sectoral specialization of regions, and particularly on regional labor market outcomes, received special attention (Izraeli and Murphy, 2003; Marelli, 2006). Considering the US case, they conclude that an increase in industrial diversification results in a decrease of regional unemployment. Longhi et al., (2005) pinpoint the degree of centralization of collective bargaining institutions as a key determinant of the strength of the relationship between regional specialization and regional unemployment. They observe that this relationship is stronger in countries with intermediate collective bargaining institutions in comparison to countries with centralized collective bargaining institutions, and advocate that policies aiming at fostering regional diversification may be gainful only in these countries. Moreover, Vamvakidis (2009) provides empirical evidence that promoting a low regional wage differentiation, a centralized wage bargaining system engenders high regional employment differentiation. However, Galbraith and Garcilazo (2007)conclude the non-existence of a trade-off between pay inequality and unemployment rate.

During the mid to late 1980s, many authors failed to quantify the contribution of structural changes to aggregate unemployment (Layard et al.,1991). On the one hand, they made the assumption that the change in pattern of unemployment can be simply decomposed into structural and macroeconomic components. However, since measuring structural change by sectoral turbulence indices ignores differences in cyclicality among sectors, sectoral shifts and aggregate movements cannot be convincingly separated (Lilien,1982). On the other hand, many structural changes have resulted in nothing more than temporary disequilibrium, though they treated them as shifting the equilibrium unemployment rate.

Actually, since Lilien (1982), structural change has been perceived as a key factor in explaining spatial disparities in labor market performance. Economic integration processes, presented as one of the major sources of structural change, are likely to initiate massive reallocation of labor resources, or sectoral shifts. Workers, displaced from declining industries, take time to be absorbed into the new expanding sectors of the economy, leading to growing regional unemployment.

According to Lilien (1982), departing from the assumption that sectoral shifts are a consequence of idiosyncratic shocks hitting some sectors/regions more than others, cross-industry dispersion of employment growth rates, as measured by the Lilien index, would positively affect the aggregate unemployment rates over time. Later, this evidence has been supported by many other studies (Samson, 1985; Barbone, Marchetti and Paternostro, 1999; Krajnyak and Sommer, 2004; Newell and Pastore, 2006; Robson, 2009; Pastore et al., 2011 ; among others).

However, according to Abraham and Katz (1986), regional unemployment differentials are the consequence of common shocks rather than idiosyncratic disturbances. Consistently, the spatial variability in sectoral shifts results as asymmetric consequences of these aggregate shocks. In order to track down the effects of aggregate disturbances, many authors (Neumann and Topel, 1991; Chiarini and Piselli, 2000; Robson, 2009; Pastore et al., 2011) included a measure of industrial diversity (e.g., Herfindhal and Gini indexes) along with the Lilien Index.

In fact, common shocks may generate asymmetric effects across industries. On the one hand, regions highly specialized in low-sensitive industries are less vulnerable to aggregate disturbances and vice versa. On the other hand, inter-sectoral mobility would be easier to operate in diversified economies, which, consequently, allows the absorption of the adverse labor market effects of common shocks (Simon, 1988; Simon and Nardinelli, 1992; Elhorst, 2003; Ferragina and Pastore, 2008). While Jacobs (1969) argues that sectoral diversification offers more job opportunities and, thus, reduces the unemployment rate, Marshall (1890) advocates specialization rather than diversification as a mechanism leading to local growth (Pastore et al., 2011).

However, according to Beaudry and Schiffauerova (2009), determining whether local labor market dynamics benefit more from specialization or diversification, depends on the time period, the level of aggregation (sectoral and territorial), the measurement method and the methodology of the analysis carried out.

3. Vulnerability to Sectoral Shifts and Diversification/Specialization Levels

Many authors have been studying the effects of sectoral shifts and industry specialization patterns on local unemployment. In this paper, we aim at assessing these effects on regional unemployment in Tunisia over the sample period (2004-11). We used the Lilien and the Gini indexes to measure the regional vulnerability to sectoral shifts and the regional level of specialization (diversification), respectively. Figure 1 shows that throughout the period of 2005-11, the western regions, and the south-east region till 2007, exhibited higher vulnerability to sectoral shifts than coastal regions. In the post-revolution period, while it has been increasing in six out of the seven Tunisian macro-regions, vulnerability decreased in the north-west region - the pre-revolution's most vulnerable region.

In the post-revolution period, we observe some mobility in the ranking of regions (Figure 2). For instance, on the one hand, the Great-Tunis and north-west regions have been improving their relative position, and, on the other hand, the center-east and south-west regions' vulnerability has been increased. However, the western regions have, all-in-all, exhibited higher vulnerability to sectoral shifts.

The industry specialization patterns may allow us to further explore these issues. In Figure 3, the Gini index suggests that the north-west and center-west regions are characterized by lower diversification. Conversely, the Great-Tunis has the highest degree of diversification.

Figure 4 corroborates these facts. In fact, almost no ranking mobility was observed during the study period. While, Great-Tunis has had the most diversified labor market, the western regions disposed the most specialized labor markets.

Actually, if diversification lessens the regional vulnerability to sectoral shifts, we would have observed a positive correlation between the Lilien and the Gini indexes. Contrarily, if further specialization lower vulnerability, we would have observed a negative correlation between these two indexes. We find a small positive correlation (0.377) between the Lilien and Gini indexes, which gives evidence that, in Tunisia, specialization would increase vulnerability to sectoral shifts, at least partially. However, in Figures 5-11, the eastern regions, and particularly the center-east, derogate to this rule and higher diversification induced higher vulnerability. Indeed, we report a negative correlation (-0.790) in the center-east. Also, the Lilien and Gini indexes were significantly and positively correlated with the unemployment rate; 0.445 and 0.297, respectively.

To sum up, on the one hand, the interior regions are the most vulnerable to sectoral shifts and they exhibit the lowest sectoral diversification, and on the other hand, both the Lilien and the Gini indexes are positively correlated with the unemployment rate. In accordance with Simon and Nardinelli (1992), we have observed a positive effect of diversification on unemployment, which meant that diversification mechanisms may favor, at least partially, employment. However, this rule does not apply to eastern regions, and particularly the center-east. We, thus, suspect that some Marshallian externalities may be at work (i.e., once a certain threshold of the degree of specialization has been reached), and they have been softening diversification induced effects on unemployment. In next sections, we will further explore these issues.

4. Exploratory Analysis

4.1 Measure of labor market performance

The preceding sections have outlined the evidence on the effects of sectoral shifts in the pre-/post-revolution periods on the Tunisian labor market. This section aims to look deeper into the preliminary evidence. We also focus on the relationship between unemployment growth rate ($URGR$), and the supply-demand mismatch (SDM), sectoral shifts ($Lilien$), the degree of specialization/diversification ($Gini$) and the density growth rate in the labor market cohort ($CDensGR$).

Regional labor market performance is measured in terms of unemployment rate dynamics. We use INS data to construct our dependent variable, $URGR_{it} = 100 * \frac{UR_{it} - UR_{i(t-1)}}{UR_{i(t-1)}}$, where UR_{it} is the unemployment rate of region i $(i = 1,2,\ldots,7)$ in year t $(t = 2005,2006,\ldots,2011)$. Figure 12 reports the regional evolution of unemployment growth rate. We document a strong heterogeneity across spatial units in terms of unemployment rate dynamics.

The supply-demand mismatch is devised as the difference between employment growth rate and labor participation growth rate. Unemployment would decline whenever the labor demand exceeds the labor supply. Thus, we expect a negative sign for this regressor. Figure 13 shows the regional evolution of this variable. It depicts an unemployment growth rate's reverse curve.

In order to capture the vulnerability of sectoral shifts, we computed the Lilien index of variance in industry employment growth (see Section 3). As documented in Section 3, higher values of the Lilien index are expected to raise unemployment growth rate, particularly in the economically weakest regions. The expected sign for Lilien is, thus, positive.

In reference to Abraham and Katz (1986), a proper modeling approach needs to disentangle sectoral shifts and aggregate disturbances. Accordingly, Neumann and Topel (1991) assert that the Lilien index may track down genuine sectoral shifts if, and only if, a measure of the degree of industrial specialization was included in the set of regressors. In this research, we used the Gini index. As discussed in Section 3, we expect a positive sign for this variable; however, Marshallian externalities may soften or reverse this effect.

The $CDensGR$ was measured as the ratio between the cohort size, or total number of individuals aged between 15 and 64, and the square kilometers. As the labor market gets larger and denser, it is expected to acquire higher degree of efficiency in the matching process and to lessen unemployment (Elhorst, 2003). However, it may also capture congestion effects and favor higher unemployment (Niebuhr, 2003). On the other hand, growth rate differentials are possible outcomes of workers mobility from lower employment regions to higher employment regions or the rejuvenation process of the cohort, which favors newcomers' massive entry to the labor market. Figure 14 depicts the ambiguous regional evolution of cohort's density growth rates. Different paths are presented in this figure. However, a negative (positive) relationship between cohort's density growth rate and unemployment growth rate (supply-demand mismatch) suggests workers mobility and/or low intra-cohort evolution, and the reverse relationship suggests intra-cohort expansion and/or the weakness or absence of workers mobility.

4.2 Exploratory Spatial Data Analysis

We used Harris-Tzavalis' unit-root test since it corrects for small samples. In reference to Table 1, we reject the null hypothesis and conclude that panels are stationary.

Table 2 pinpoints the existence of spatial autocorrelation. We thus consider the Geographic Weighted Regression (GWR), which is a powerful technique for exploring spatial heterogeneity. This technique allows us to test whether spatial non-stationarity exists and whether or not the structure of the process being modeled varies across the study regions.

4.3 Resolving Multicollinearity

Collinearity - multicollinearity if more than two predictor variables - is where two variables in a statistical model are linearly related (Alin, 2010). According to Stewart (1987), Belsley (1991) and Chatfield (1995), many statistical routines are sensitive to collinearity. Collinearity fathers unstable parameter estimates, inflated standard errors on estimates and consequently biased inference statistics. Meloun, et al. (2002) evidence that under collinearity, variable effects cannot be separated and extrapolation is likely to be seriously erroneous. Collinearity is, thus, often recognized as a special case of model non-identifiability (Dormann et al., 2012). Besides, many authors have also raised the ambiguous impact of changing collinearity structures over time and space.

Collinearity arises for several reasons, and numerous studies have not embraced measures to address these issues. The naÃ¯ve examination of the correlations matrix, reports highly correlated variables, which reveals a multicollinearity problem. We, thus, expect coefficients' inflated standard errors (Wheeler, 2007); resulting in inaccurate tests of significance for the predictors, and important predictors may, then, be found non-significant, even if they are truly influential (Ohlemüller et al., 2008).

Although correlation and collinearity are not the same, several authors have been using correlation as an indicator for collinearity. They argue that high absolute correlation coefficients usually indicate high linear relatedness. In other words, these variables may share substantial amounts of information; revealing a collinearity problem. Later, we used the variance inflation factor (VIF) to quantify the severity of multicollinearity; measuring the extent of the variance of an estimated coefficient would be increased because of collinearity.

Several methods have been proposed to resolve multicollinearity: (1) identify which variables are clustering together, then form a proxy-set (principal component analysis, cluster analysis, and iterative variance inflation factor analysis), (2) get from the collinear input to the non-collinear output data, or cluster-independent methods (Sequential regression), (3) model with latent variables (principal component regression, partial least squares, penalized partial least squares, constrained principal component analysis, latent root regression, and dimension reduction), and (4) use tolerant methods (penalized regressions, octagonal shrinkage for clustering and regression, machine-learning methods, and collinearity-weighted regression).

In this paper, we have to deal with variations in multicollinearity structures in both time and space. We, thus, operated both a dynamic factorial analysis (DFA) and a sequential panel regression. Although, the DFA (Federici and Mazzitelli, 2005) achieved a high extraction level (more than 89%), the resulting factors lack interpretability. On the other hand, Dormann et al. (2012) claimed a sequential approach (Graham, 2003) as one of the methods worthy of further exploration. Interpreting the sequential approach requires careful wording and head-scratching; however, it represents two arguments over the DFA: (1) there is no longer a non-extracted variability, and (2) it is really close to our intuitive understanding of the variable.

4.4 Sequential panel approach

Graham (2003) devised a sequential regression to create new, cleaned-up explanatory variables by reciprocally subtracting the common variation from the less important variables. This method is sometimes called residual regression, not to be confounded with the rightly criticized approach of regression of residuals (Freckleton, 2002). While in sequential regression the predictors are regressed, in "regression of residuals" the residuals of the independent variable are used in a second-step regression.

The sequential approach is typically divided into two steps: (1) classifying independent variables in a sequence of importance, and (2) calculating the independent contribution of each explanatory variable. The resulting variables are then orthogonal, but conditional and cannot be interpreted without the previous ones. This, conceptually, meets path analysis methods where variables act through their relationships with other variables (Grace, 2006).

Table 3 reports the order of importance and the underlying conditional path. Consequently, the first variable (*CDensGR*) will remain as it is. The second variable (*Gini*) will be regressed against the first, and the residuals will represent its independent contribution. The third variable (*Lilien*) will then be regressed against the first and the residuals of the second, and so forth.

Each variable was, then, replaced by its independent contribution. Thus, inferring in this context require a deeper attention to the interpretation of variables changes.

5. Cross-Sectional Models

5.1 Unemployment dynamics: year-to-year comparison

First, we set up yearly exploratory cross-sectional models throughout the study period (2005-11). We employ, as dependent variables, the unemployment growth rate, and, as independent variables, the Lilien and Gini indexes, the supply-demand mismatch, and the density growth rate of the cohort.

In Table 4, the global model shows that all the dependent variables are significantly related to *SDM*. As expected, its sign was negative. The *SDM* refers to the ability of the regional labor demand to provide new jobs that exceed the number of newcomers, and, partially, contribute to unemployment decline, conditional on the labor supply growth rate or evolution, the regional degree of specialization and region's vulnerability to sectoral shifts.

The *Gini* was significant in 2005, 2006 and 2011. However, we observe different signs, which meant that some Marshallian externalities were at work and they soften diversification induced effects on unemployment in 2007 and 2008 and manage to reverse it in 2005, 2009 and 2010. Table 4 suggests that in 2005 the higher local base of a given industry, the lower the growth of unemployment rate given the cohort's newcomers. It documents a positive effect of diversification on unemployment in 2006 and 2011. Accordingly, diversification within a geographic region raise the likelihood for dismissed workers to find employment in other sectors given the cohort's newcomers, or new-competitors.

In reference to the conditional path (see Table 3), the *Lilien* refers to region's degree of vulnerability to sectoral shifts given the labor supply evolution and the regional degree of diversification (specialization), which enables the *Lilien* to capture genuine sectoral shifts. Table 4 indicates that, in 2010 and 2011, sectoral shifts subserve unemployment growth.

Last, and not least, the *CDensGR* is found significant in 2011 and, to a large degree, contributes to the post-revolution unemployment growth. The arrival of newcomers, particularly in the northern and south-east regions, give rise to a congestion effect hugely contribute to increasing the unemployment growth.

Only for 2009, the test of the bandwidth suggests that the geographically weighted regression model is a significantly better model for unemployment growth than the global linear regression model. The significance tests for non-stationarity of the parameter estimates reject the non-stationarity hypothesis at the 5% level. However, test has found significant, at the 10% significance level, twice in 2007 and 2008, which suggests that *SDM* may vary across regions. On the other hand, Table 4 documented an improvement in the variance inflation factor when we used the sequential approach, as the average observed *VIF* got closer to 1.

5.2 Exploring regional evolution of unemployment dynamics

According to Figure 15, while the center-east and Great-Tunis regions have had the largest cohort growth, the north-west has had the smallest over the period of time (2005-11). As expected, interior regions exhibited higher vulnerability to sectoral shifts and higher level of specialization. However, unlike the center-west, the north-west shows a higher supply-demand mismatch and a lower unemployment growth rate. This argument supports our sequential approach. In fact, conditional paths are more intuitive and allow to filter genuine effects.

A two-steps cluster analysis (Figure 16) suggests two clusters of regions: the first includes the western and south-east regions, the second includes the Great-Tunis, north-east and center-east regions. The second group has an overall lower vulnerability, higher diversification, higher labor supply growth and higher labor demand growth.

The principal component analysis (Figure 16) achieved a high extraction level of 94.8%. The first principal component (52.4%) is strongly correlated with the cohort's density growth and the Gini index. This suggests that these two criteria vary together. Otherwise, an increase in cohort density may favor diversification, and an increase of specialization may slow down cohort growth, and vice versa. This component can be viewed as a measure of workers mobility from low diversification regions towards high diversification regions. The second principal component (42.4%) can be viewed as a measure of the ability of the local labor market to create new jobs for newcomers and, partially, the unemployed given the regional sectoral shifts. Higher labor market vulnerability to sectoral shifts results in poorer labor demand, and vice versa.

We observe that all regions in cluster 2 were those with higher labor demand growth/lower vulnerability and higher labor supply growth/higher diversification. The center-west and south-west regions were those with higher vulnerability/lower labor demand growth and higher specialization level/lower labor supply growth. The south east has the highest vulnerability/poorest labor demand growth and higher diversification/higher labor supply growth. Finally, the north-west has the highest specialization level/lowest labor supply growth and the highest labor demand growth/lowest vulnerability to sectoral shifts. The principal component analysis sides the sequential approach; confirming our intuitive understanding of the independent variables. The latter, however, has the advantage of being time invariant.

In Table 5, the average unemployment growth rate in the period of time $2005-11$ is regressed on the $2005-11$'s respective averages of the independent variables ($CDensGR$, $Gini$, $Lilien$ and SDM). In this period of time, the cohort growth induced a congestion effect and, thus, higher unemployment. In other words, we expect higher outgoing mobility and lower intra-region's cohort growth rate to favor unemployment decreases, and higher incoming mobility and/or higher intra-region's cohort growth rate to engender a congestion effect and, thus, higher unemployment growth.

In reference to Table 3, the $Lilien$ measures real sectoral shifts given the regional specialization level and the labor supply evolution. These sectoral shifts have contributed to unemployment rate growth (see Table 5).

Finally, SDM significantly lessens unemployment growth, which means that the regional labor demand contributes to unemployment decline as it creates enough new jobs for newcomers and some unemployed, given the labor supply evolution, the regional degree of specialization and region's vulnerability to sectoral shifts.

The test of the bandwidth suggests that the geographically weighted regression model and the linear regression model are equivalent. While the significance tests for non-stationarity of the parameter estimates reject the non-stationarity hypothesis for all the independent variables.

Using the sequential approach described in Section 4, the *VIF* has dropped down from 34.110 to 1.010.

5.3 Exploring regional evolution the pre-/post-revolution of unemployment dynamics

In this section, we attempt to compare the pre-/post-revolution's unemployment dynamics. We, thus, devised two exploratory cross-sectional models: pre- and post-revolution models. We employ, as dependent variables, the unemployment growth rate, and as independent variables the Lilien and Gini indexes, the supply-demand mismatch, the density growth rate of the cohort and the initial conditions.

Initial Conditions ($UR04$ and $UR10$). We include the unemployment rate at the beginning of the period to control for local labor market conditions. These variables have been highly correlated with the other independent variables. Thus, Table 6 reports new conditional paths, where we control for initial conditions in the first-level of the sequential approach.

In Figures 17 - 18, we observe that the pre-revolution interior regions have the highest levels of specialization and of vulnerability to sectoral shifts. However, the north-west and center-west regions have lower labor supply growth and higher labor demand growth compared to southern regions. The latter have the highest pre-revolution unemployment growth.

In post-revolution, while the south-east has increased its diversification level, the north-west has decreased its vulnerability to sectoral shifts. Besides, while the south-west has the least labor supply growth, the center-west has the lowest labor demand growth. The Latter experiences the highest post-revolution unemployment growth. On the other hand, the north-west and south-west regions have among the lowest unemployment growth in the country.

Figures 19 - 20 report two clusters of regions: The first cluster includes the coastal and south-west regions, the second includes the north-west and center-west regions. The second group has an overall higher specialization level, lower labor supply growth, higher labor demand growth and higher vulnerability to sectoral shifts. The first cluster includes the coastal and north-west regions, the second includes the center-west and south-west regions. The second group has an overall higher vulnerability to sectoral shifts, lower labor supply growth, higher specialization and lower labor demand growth.

The pre- and post-revolution principal component analysis (Figures 19 - 20) both achieved high extraction levels of 92.9% and 83.1%.

The first principal component (56.2%) is strongly correlated with the cohort's density growth, the Gini index and the supply-demand mismatch. This suggests that these criteria vary together. Otherwise, an increase in labor supply growth may simultaneously promote diversification and labor demand growth, and vice versa. This component measures workers mobility from low diversification regions towards high diversification regions. It also suggest that larger and denser regions are expected to exhibit higher degrees of efficiency in the matching process (Elhorst, 2003). Finally, this component implies that diversification favors labor demand growth. The second principal component (36.7%) measures the regional vulnerability to sectoral shifts. We observe that higher vulnerability is associated with a lower diversification level and, thus, lower labor demand growth. We observe that regions in cluster 2 were mainly those with highest vulnerability to sectoral shifts.

The first principal component (47.1%) is strongly correlated with the cohort's density growth, the Gini and Lilien indexes, and the supply-demand mismatch. Otherwise, an increase in specialization would induce increased vulnerability to sectoral shifts, which would slow down or reverse labor demand growth. This component depicts the Portfolio theory. The second principal component (36.0%) measures the local labor supply growth. Figure 23 portrays a congestion effect (Niebuhr, 2003). Regions in cluster 2 were those with the highest vulnerability to sectoral shifts/highest specialization level and, thus, lowest labor demand growth.

Table 7 points to the existence of spatial autocorrelation both in pre- and post-revolution. The Geographic Weighted Regression (GWR) allows us to check the pre-/post-revolution spatial heterogeneity.

In Table 8, the average unemployment growth rate in the pre- and post-revolution ($UR5GR10$ and $UR10GR11$) are regressed on the respective averages of the set of independent variables mentioned in Section 4 ($CDensGR$, $Gini$, $Lilien$ and SDM) and unemployment rate at the beginning of the correspondent period ($UR04$ and $UR10$).

In contrast to the pre-revolution, we observe unemployment persistence and congestion effects in the post-revolution (Table 8). By controlling for the local labor market conditions, we observe residual supply growth non-motivated by mobility from higher-unemployment to lower-unemployment regions.

The $Lilien$ measures a real sectoral shifts given the regional specialization level, the labor supply evolution and the local labor market initial conditions. These sectoral shifts have contributed to unemployment rate growth in both pre- and post-revolution periods (see Table 8). However, Table 8 suggests that this effect was higher in the post-revolution period. Finally, SDM is found significant in both pre- and post-revolution periods. It has largely contributed to reducing unemployment growth, particularly in the post-revolution.

The significance tests for non-stationarity of the parameter estimates reject the non-stationarity hypothesis for all the independent variables, at the 5% significance level. Using the sequential approach described in Section 4, the VIF has dropped down from 25.080 in the pre-revolution period and 18.140 in the post-revolution period to 1.090 and 1.030, respectively.

All-in-all, Table 8 suggests that congestion effects in the post-revolution period were the principal cause of unemployment growth. It also reports an unemployment persistence phenomena and an increased impact of sectoral shifts in post-revolution. In the next section, a dynamic econometric model will further explore these issues and regional spillovers.

6. Econometric Analysis

6.1 Model specifications

In this section, we study the relationship between unemployment growth and its main determinants throughout the pre- and post-revolution periods. Anselin (1988) asserts that analyzing the spillovers should be the principal focus in spatial modelling. Both the agglomeration effects (Overman and Puga, 2002) and unobserved heterogeneity clustered in space (Niebhur, 2003; LeSage and Pace, 2009) beget spatial dependence. Accordingly, omitting spatial autocorrelation leads to misleading estimates and inference. Furthermore, these dependencies does not only occur in the dependent variable, but also on the independent variables. We thus resort to the Spatial Durbin Model.

The Spatial Durbin Model is appealing because a distinction can be made between the direct impact and the indirect impact of a change in an explanatory variable. It often advisable when we are concerned about omitted variables. It also yields to unbiased parameters even if the true Data Generating Process is, among others, the Spatial Error Model or the Spatial Lag Model.

According to Pastore et al. (2011), nonlinearities are likely to occur in the relationship between unemployment growth and its determinants. Moreover, we suspect heteroscedasticity. Thus, we compute, in this section, the unemployment growth rate for the i^{th} region in the period t ($URGR_{it}$), based on the natural logarithmic transformation of the unemployment rate. Similarly, we construct the cohort's density growth rate ($CDensGR_{it}$) and the supply-demand mismatch (SDM_{it}). The Lilien and Gini indexes were devised as described in Section 3. We, then, added the labor market initial conditions ($LUR04_i$); natural logarithmic transformation of the unemployment rate in 2004, and the revolution dummy ($Revolution_t$) which takes 1 in 2011 and 0 everywhere else.

6.2 Data and assumptions

Table 9 reports Farrar-Glauber Multicollinearity tests. The Chi-square test points multicollinearity problems. And according to the F-test, multicollinearity has been affecting all the independent variables. The Farrar-Glauber Multicollinearity t-Test (Table 10) validates our sequential approach (Figure 20). The time invariant variable ($LUR04$) and the Space-invariant variable ($Revolution$) will remain as they are (see Table 11).

Table 12 reports the results of the sequential approach. The labor supply growth increases as the initial unemployment rate increases. Based on INS data, regions with a higher unemployment rate are those with higher population growth and a higher share of younger people.

Specialization increases in the high-unemployment regions, and especially after the advent of the revolution. Besides, although statistically non-significant, it seems that the labor-supply growth, given the initial labor market conditions, favors diversification as denser regions may exhibit a higher degree of efficiency in the matching process (Elhorst, 2003).

Vulnerability to sectoral shifts also increases in high-unemployment regions and even more after the revolution. Seemingly, the labor supply growth, given the initial labor market conditions, may reduce a region's vulnerability to sectoral shifts; toughening matching process, the *Gini* indicates that higher specialization, given the initial labor market conditions, the advent of the revolution and the labor supply growth, induces higher vulnerability to sectoral shifts.

Finally, the supply-demand mismatch or the ability of the labor market to provide enough jobs for newcomers and to partially eradicate unemployment, have been reduced after the revolution. Similarly, congestion effects, specialization and vulnerability to sectoral shifts seem to exert detrimental effects on the supply-demand mismatch.

The panel non normality test (Table 13) confirms the absence of non-normality problems. However, in spite of the logarithmic transformation, the panel data heteroscedasticity tests (see Table 13) suggest the persistence of heteroscedasticity problems. Besides, in order to test for endogeneity problems, we first run a Spatial Durbin Han-Philips linear dynamic panel data regression, then save residuals and re-run again but this time we include residuals in the model. If residuals were found significant, this means that we have an endogeneity problem, otherwise we reject the endogeneity problem hypothesis. However, we would expect no endogeneity problem using a sequential approach. Indeed, one other appealing feature of a sequential approach is eliminating endogeneity. Also, our devised test shows no endogeneity problem.

6.3 Homoskedastic approach and diagnostics tests

Mankiw (1990) and Gujarati and Porter (2009) argue that heteroscedasticity does not systematically imply rejecting a good model. Accordingly, we propose in this section to examine an homoskedastic Spatial Panel Durbin Model (LeSage and Fischer, 2008; LeSage and Pace, 2009). Belotti, Hughes and Mortari (2013)reported a global higher performance of this approach over other homoskedastic concurrent approaches.

Table 14 provides estimation results and diagnostics tests for the homoskedastic model applied to analyze the spatial effects characterizing unemployment dynamics in Tunisian macro-regions. After considerable experimentation, we have resolved to remove the spatial lag for the independent variable "Revolution."

Per the Hausman tests (see Table 14), we retain the random-effects model. The Spatial Autoregressive Model (SAR) test for spatial lag effects signals that neighboring units exhibit a higher degree of contagion than do units located far apart. However, the spatial Rho estimate, provided in Table 14, evidences small, but significant, spatial dependence. We suspect macro-aggregation to have reabsorbed some of the spatial dependence.

The Spatial Error Model (SEM) test supports the existence of spatial error autocorrelation. While the Spatial Durbin Model's specification has been able to explain about 90% of the overall variation in unemployment growth; nearly 90% and 96% percent in within and between variations, respectively, the R-squared of the Spatial Autoregressive Model with Autoregressive Disturbances (SAC) has barely reached 38%. Therefore, we have opted for the Spatial Durbin Model with Random-Effects.

In Table 14, neither the time-lagged dependent variable nor the intercept were significant. As expected, the revolution has aroused the unemployment growth both locally and in neighboring regions. We document significant direct and indirect effects of the revolution. Seemingly, the revolution has locally fostered unemployment growth, but the inter-regions' shockwave effect has been further increasing this growth.

Pastore et al. (2011) observed that regions with higher initial unemployment are more likely to reduce the unemployment rate rather than other regions up to a threshold. Once they reached a maximum level, initial conditions do not have effect on unemployment growth. Overman and Puga (2002) argued that regions with an initial high or low unemployment rate saw little changes, while those with an intermediate level of initial unemployment rate moved towards extreme values.

Table 14 shows that the initial conditions ($LUR04$) do not have either direct or indirect effects on local unemployment growth. Although initial conditions do not generate either decline or persistence effects, results, in Table14, acknowledge that they may restrain unemployment growth in neighboring regions. Presumably, this effect is the result of a bipolarisation mechanism.

Elhorst (2003) asserts that labor supply growth may favor matching efficiency and, thus, unemployment decline. On the contrary, Niebuhr (2003) fears a congestion effect, which may increase unemployment rate. On the other hand, neo-classical authors argue that workers move from initially high-unemployment regions towards prosperous regions; reducing regional differences in unemployment rates.

In Table 14, the labor-supply growth given the initial regional unemployment rate and the advent of the revolution is found to significantly impact unemployment growth. Indeed, we observe a combination of the above-mentioned effects. First, the direct effect documents a congestion effect. Second, although the labor supply growth locally increases unemployment growth, neoclassical mechanisms may explain the opposite effect observed for neighboring regions. Third, in reference to the indirect effect, workers keep moving from high unemployment towards low unemployment regions till a congestion effect occurs in these regions and restrains mobility. Finally, we presume, although the total effect was non-significant, that, at this level, labor supply growth would foster matching efficiency, thereby braking unemployment.

Gini refers to the diversification level given the initial unemployment rate, the advent of the revolution and the labor-supply growth. Table 14 documents the absence of direct and indirect effect of the Gini on the unemployment growth. As hypothesized by Pastore et al. (2011), reaching a certain specialization threshold, Marshallian externalities gain relevance and, thus, the specialization effect on unemployment growth is not statistically significant in highly specialized regions. However, we observe, once again, a bipolarisation effect; regions with higher initial unemployment rate and lower labor supply growth develop higher levels of specialization, favor diversification in neighboring regions with lower initial unemployment rate, denser cohort - seemingly favored by mobility – and a higher degree of efficiency in the matching process, and, thus, reduces unemployment growth in its neighbors.

In reference to Table 12 , the sectoral shifts effects may be softened in initially lower-unemployment regions that have achieved a comparatively high level of diversification and high degree of efficiency in the matching process; otherwise, regions may exhibit higher vulnerability and, thus, pro- unemployment growth mechanisms (see Table 14). However, induced polarisation effects result in lower unemployment growth in neighboring regions that have a lower initial unemployment rate, higher labor-supply growth, higher diversification and are consequently less vulnerable. Besides, vulnerability and polarisation may induce an opposite feedback effect, which favors mobility to prosperous regions and, thus, lower the labor supply's pressure and initiate a braking mechanism of unemployment growth.

Finally, the ability of the labor market to provide enough jobs for newcomers and to partially eradicate unemployment, in spite of the braking mechanisms initiated by the advent of the revolution, congestion effects, specialization levels and vulnerability to sectoral shifts, have greatly reduced local unemployment growth. This contribution is even greater in regions with lower vulnerability and a more efficient matching process. However, the bipolarisation effect favoring matching in prosperous regions, through lower vulnerability and higher diversification, may induce unfair competition that may favor unemployment growth in less fortunate regions. However, in turn, this would foster mobility toward lower-unemployment regions and give way to congestion effects, with local labor market failing to reabsorb newcomers and, thus, partially brake unemployment reduction. Generally speaking, the matching efficiency is locally at the forefront of the unemployment battle.

Unfortunately, according to Table 14 , non-normality and heterogeneity problems arise in the above model, which greatly limits our conclusions. We further address these issues in the next section.

6.4 Non-linear heteroskedastic approach: discussion and conclusions

After meticulous investigations of heteroscedasticity and non-normality concerns revealed in last section, we resort to a Log-Log MLE Spatial Panel Durbin Multiplicative Heteroscedasticity Model. Then, further model comparison and tests lead us to retain the thereafter model.

Table 15 reports significant improvements in normality and homoscedasticity. However, following the log-log transformation, the R-squared dropped to 80% and adjusted R-squared was about 69% . On the other hand, the spatial Rho suggests high spatial dependence, which evidences a higher degree of contagion between neighboring units comparatively to units located far apart.

According to Table 15, the ability of the local labor market to secure enough jobs for newcomers and, partially, the unemployed, despite the slowdown triggered by congestion effects, specialization levels and vulnerability to sectoral shifts, particularly in the post-revolution period, solely contributes to local unemployment reduction. Moreover, Table 15 reports spillovers of the initial unemployment rate, the labor supply growth and the Gini index, which corroborates results discussed in the previous section. However, unemployment growth is inelastic to these variables.

Presumably, a region initially suffering from a high unemployment rate may favor mobility toward lower-unemployment neighboring regions, giving rise, in these regions, to congestion effects and consequently a higher unemployment rate (Niebhur, 2003). Later, the labor supply growth in these regions leads to higher efficiency in the matching process and favors labor market diversification. The latter increases mobility; attracting newcomers from higher unemployment regions and risking a new episode of congestion. Finally, initially disadvantaged regions would have a lower unemployment rate. The latter have to enhance their ability to create new jobs, otherwise they may resume the above-mentioned cycle. However, if they fail and the congestion effect persists in prosperous regions, so they attain a certain threshold and are not able to further develop their labor markets, unemployment may further persist.

6.5 Discussion, conclusion and further research

In this work, we present an empirical framework to assess the effects of sectoral shifts and industry specialization patterns on the regional unemployment dynamics in pre- and post-revolution periods in Tunisia.

Chiefly specialized in low-skilled labor, interior regions have exhibited higher vulnerability to sectoral shifts. Surprisingly, after the revolution, while it has dropped in the north-west, the pre-revolution period's most-vulnerable region, vulnerability peaked up in the six other regions. As mentioned in Section 3, we have to include a measure of industrial specialization in order to override the contribution of the business cycle, and to track down genuine sectoral shifts. In fact, this meant distinguishing sectoral shifts from aggregate disturbances of the business cycle. The Gini index pointed to Great-Tunis and the western regions as the most diversified and the least diversified regions, respectively.

Initial results were in accordance with Simon and Nardinelli (1992). Otherwise, we observe that diversification seems to favor unemployment reduction. However, this does not apply to the center-east region, which leads us to suspect Marshallian externalities to reverse the diversification induced effect on unemployment in these regions.

In order to set aside induced and genuine effects, we have adopted a sequential spatial approach, taking into account spatial dependencies and externalities. This approach conceptually meets the path analysis method.

Even though it evidences the existence of Marshallian externalities at work, the year-to-year perspective documents an overall positive effect of diversification on unemployment in the post-revolution period. Moreover, increased vulnerability to sectoral shifts and a congestion effects were subserving unemployment growth, particularly in the post-revolution period.

Throughout the 2004-11 period, the labor supply growth, generating a congestion effect, gives rise to higher unemployment rates. For instance, the north-west has the lowest cohort growth and, thus, lower unemployment growth. In the post-revolution period, congestion effects were the principal causes of unemployment growth, followed by the unemployment persistence and the increased impact of sectoral shifts.

Moreover, regions with initially higher-unemployment were those with low-skilled labor, higher inner-population growth, and a higher share of the young and mostly educated. In the post-revolution period, they have experienced increased specialization and, consequently, higher vulnerability to sectoral shifts.

We, however, notice the co-existence of the Elhorst (2003) and Niebhur (2003) effects of the labor-supply growth. On the one hand, labor-supply growth initiates a higher degree of efficiency in the matching process and, thus, favors diversification particularly in, initially, lower unemployment regions. On the other hand, a congestion effect occurs, which induces higher vulnerability and toughs the matching process. The latter, or the region's ability to provide enough jobs to newcomers and to contribute to unemployment eradication, has been greatly reduced by the advent of the revolution.

Our study pinpoints a high degree of contagion between neighboring regions compared to regions located far apart. For instance, when initial unemployment rate increases in a prosperous region, it limits mobility and, thus, favors congestion effect in its neighborhood, and vice-versa. On the other hand, if unemployment increases in initially high unemployment region, it may increase mobility toward its neighbors and relocate congestion effects and, consequently, unemployment growth.

Specialization in low-skilled labor in initially high-unemployment regions at the advent of the revolution, promotes high mobility toward prosperous neighbors; arousing congestion effects and unemployment growth. On the other hand, diversification in initially low-unemployment regions attracts more newcomers and, thus, reduces unemployment growth within less-prosperous neighbors.

Additionally, we notice that the cohort's density, the vulnerability to sectoral shifts and the advent of the revolution exert a detrimental effect on the supply-demand mismatch. Actually, the revolution increases vulnerability in high-unemployment regions and, thus, promotes mobility, which favors more efficient matching in less vulnerable neighbors. However, congestion effects are more persistent, especially after the revolution and, thus, dramatically affect the efficiency of the matching process, which results in persistence of unemployment. Actually, the revolution has been promoting congestion effects and higher vulnerability to sectoral shifts and, consequently, fostering unemployment growth.

To sum-up, initially high-unemployment regions have increasingly young populations, and are experiencing increases of educated and women shares. Unfortunately, these regions are particularly exposed to structural changes due to their persistent weakness: high specialization in low-skilled labor intensive activities and low industrial diversification, infrastructure level and attractiveness to foreign direct investment. Consequently, they depend on more developed regions and, thus, promote mobility toward these regions. The latter may experience congestion effects, which may result in higher unemployment rates, then further more efficient matching process. On the other hand, underdeveloped regions may first experience a higher degree of efficiency in the matching process, then if they were not able to catch up, they may revert to congestion effects resulting from their inner-labor supply growth. Back to square one, lower-unemployment regions must be still attractive and have sufficiently developed and diversified their labor market to provide enough jobs to newcomers, and particularly educated ones.

In the north-east and center-west regions, specialization seems to support unemployment growth, and according to Jacobs (1969), sectoral diversification may then offer more job opportunities and locally improve labor market performance. On the other hand, the effect of specialization on local unemployment growth, in the Great-Tunis, north-west and southern regions, is statistically non-significant. Moreover, we observe a positive effect of specialization in the center-east region, where specialization may reduce unemployment growth. In effect, after a certain threshold of specialization, Marshallian externalities gain relevance and mitigate the previous pattern.

Besides, congestion effects are mainly responsible for unemployment growth in Tunisia. The supply demand mismatch, or the ability to provide enough jobs to newcomers and partly the unemployed, fails to even the effect of the labor supply growth, except in the northern and center-west regions. While, we notice overweening congestion effects in southern regions, mobility toward more developed regions allow, at least partially, to brake unemployment growth in the north- and center west regions. The north-east region clearly exhibits a higher degree of efficiency in its matching process.

Pastore et al. (2011) reported that regions with a higher initial unemployment rate are more likely to reduce unemployment rates than other regions up to a threshold. After a maximum level, initial unemployment has no effect on unemployment growth. As expected, high initial unemployment rate has been braking unemployment growth in the center- and south-west regions, and reaching 21% in the north-west, initial unemployment rate has no longer effect on unemployment growth. O the other hand, initial low unemployment rate encourages mobility and, thus, gives rise to higher unemployment rates in the north-east regions. Even though Great-Tunis and south-east were initially low-unemployment regions, persistent congestion effects, low birth rates, high housing costs and weak labor demand have slowed down labor supply growth and, thus, evened the influx of newcomers. Also, initial unemployment reduces unemployment growth in the center-east, which suggests the reverse of Pastore et al. (2011). In other words, reaching a certain threshold, regions with a lower initial unemployment rate are more likely to increase unemployment.

Finally, the revolution boosted unemployment growth in all Tunisian macro-regions, except the center-west. However, the latter has faced a higher unemployment rate on the eve of the revolution. In other words, it was the inevitable result of an inner-process.

A fuller explanation of the polarisation effects, the reasons behind regional specialization pattern and sectoral shifts, and the determinants of regional mobility and supply shifts are left for future research.

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Figure 1: Lilien Index (2005-11)

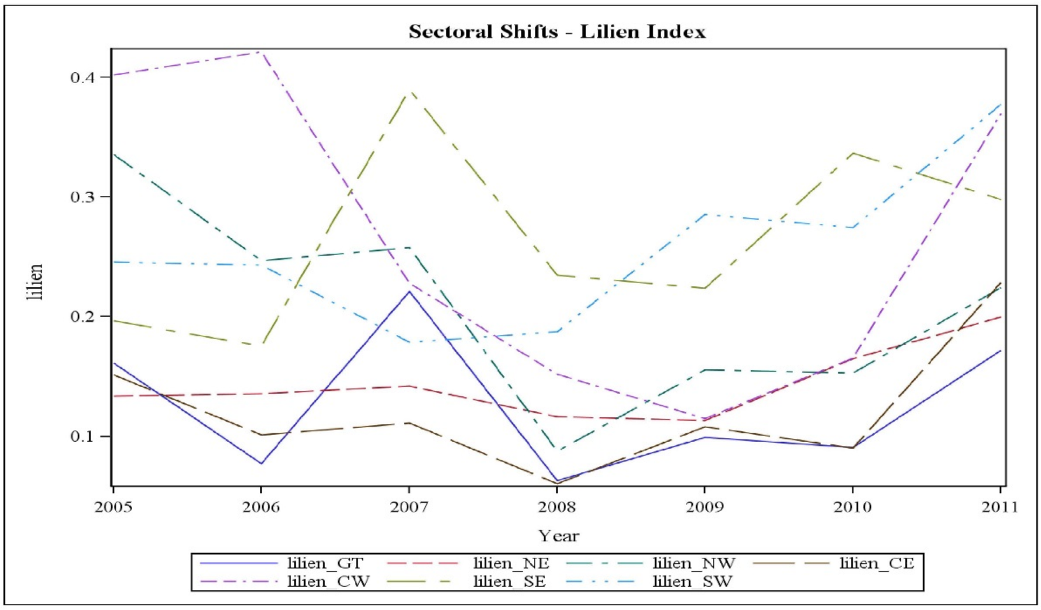

Figure 2: Lilien Index: Regional Ranking

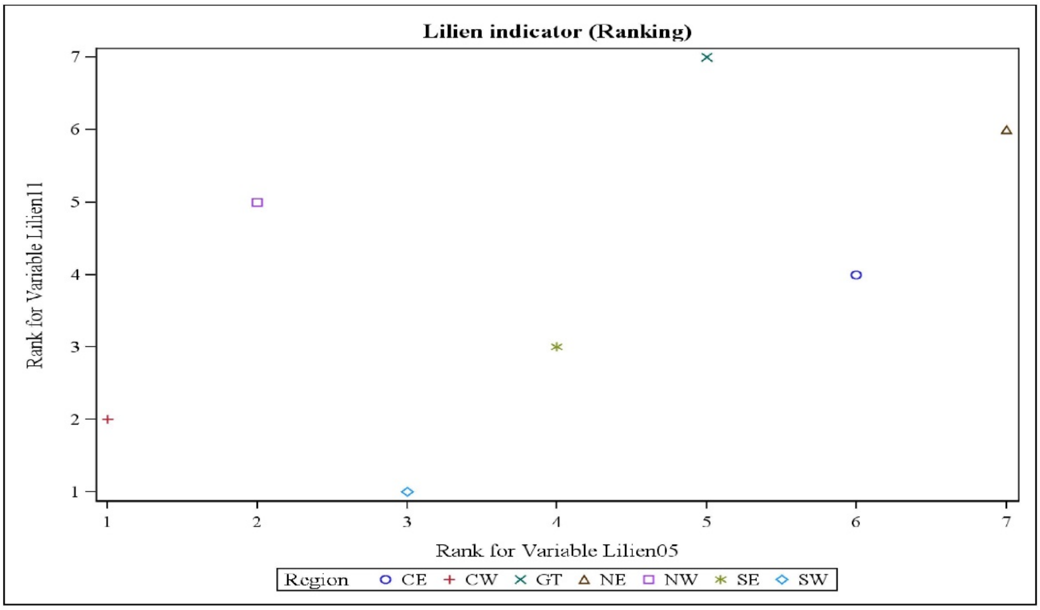

Figure 3: Gini Index (2005-11)

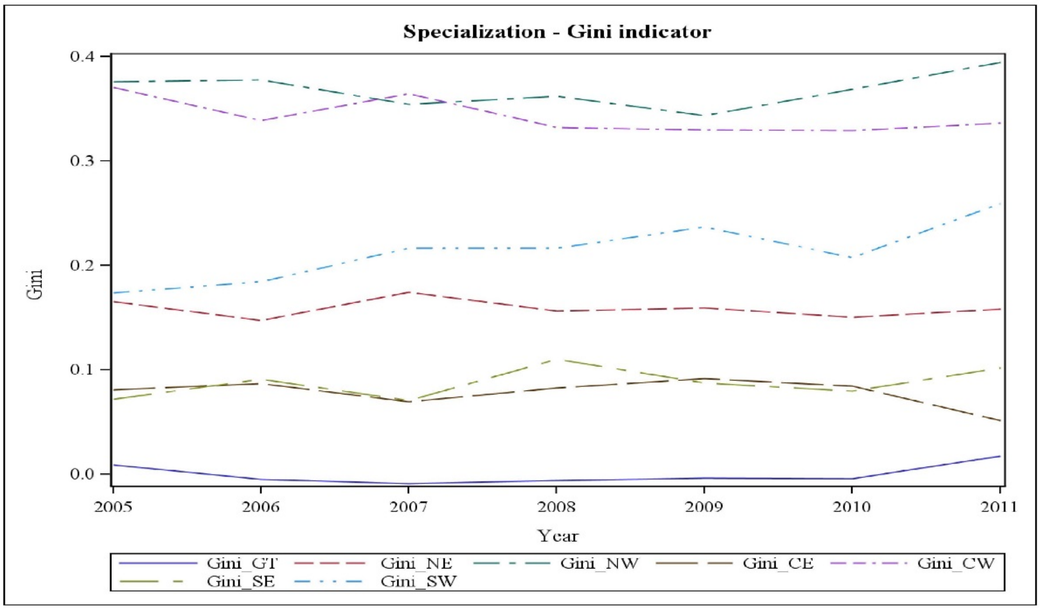

Figure 4: Gini Index: Regional Ranking

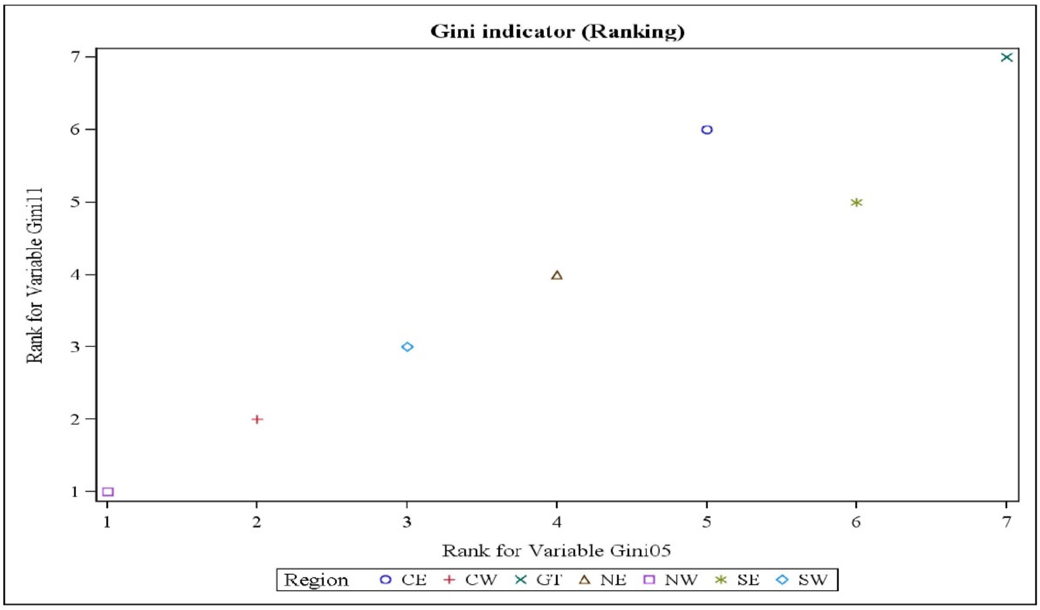

Figure 5: Lilien and Gini Indexes: Center-east

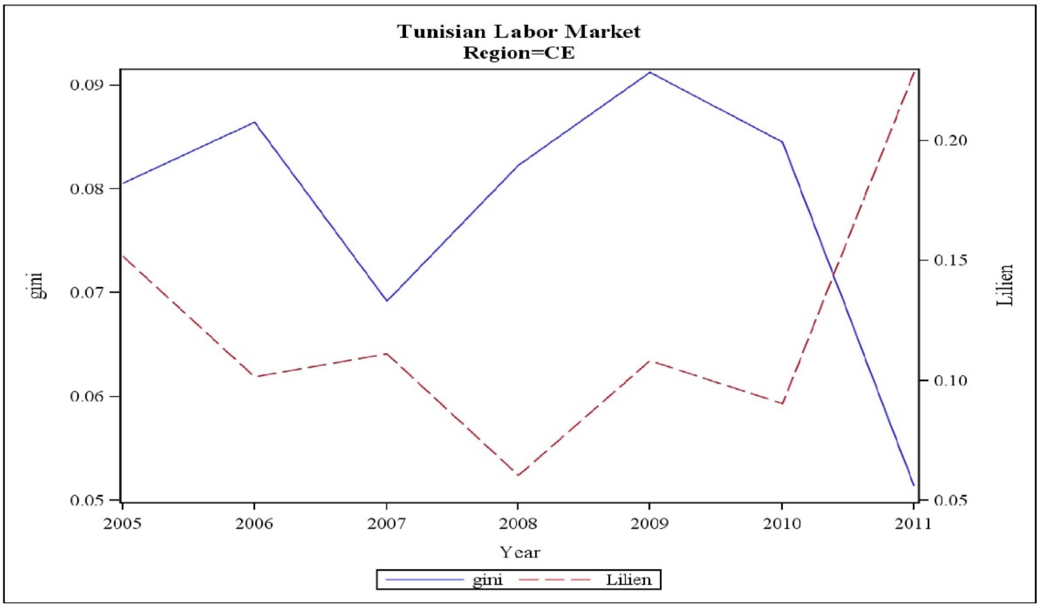

Figure 6: Lilien and Gini Indexes: Center-west

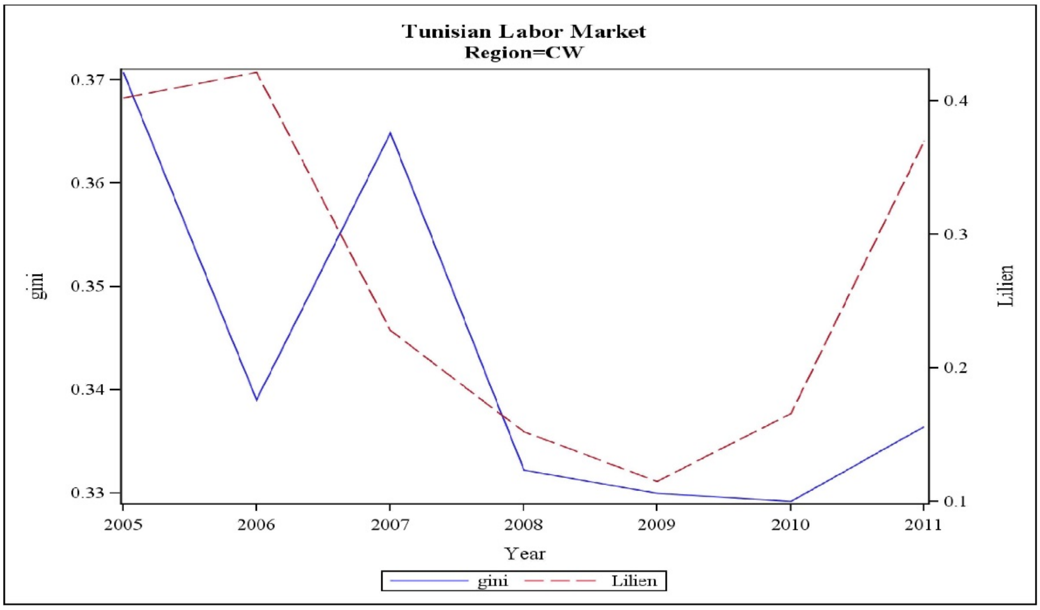

Figure 7: Lilien and Gini Indexes: Greater-Tunis

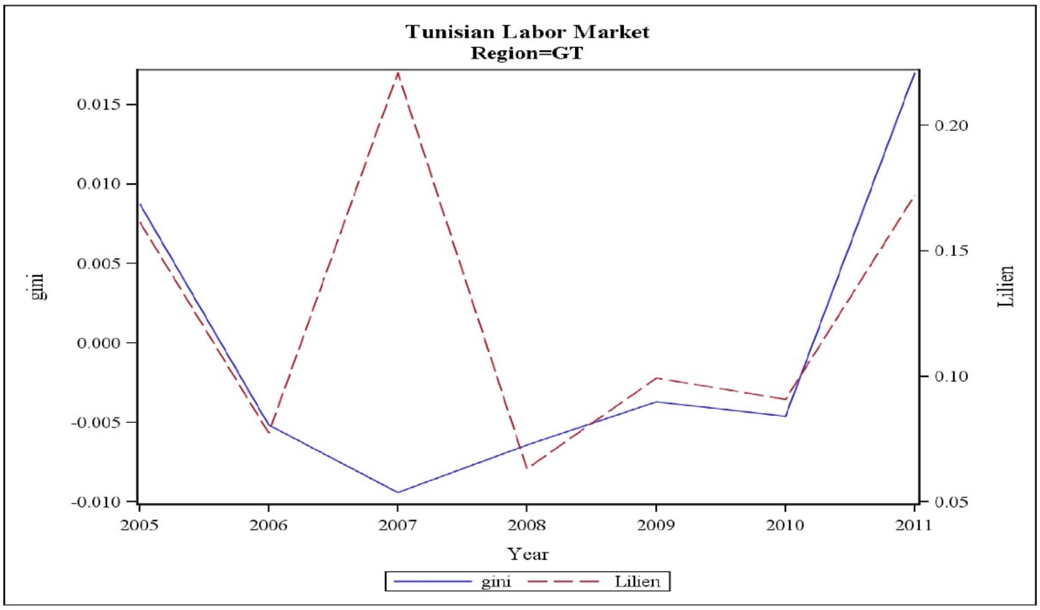

Figure 8: Lilien and Gini Indexes: Northeast

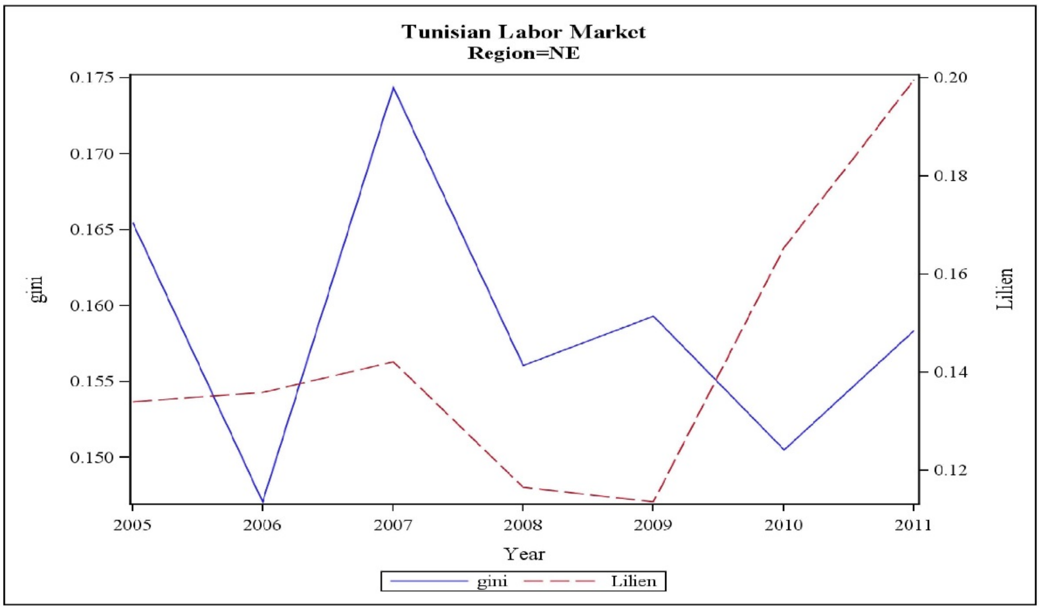

Figure 9: Lilien and Gini Indexes: Northwest

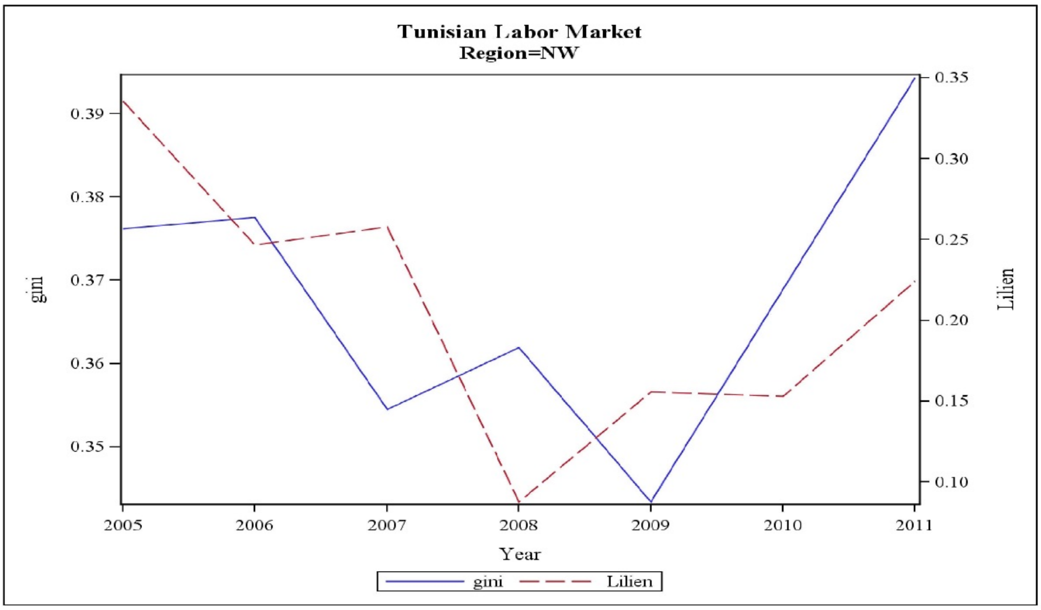

Figure 10: Lilien and Gini Indexes: Southeast

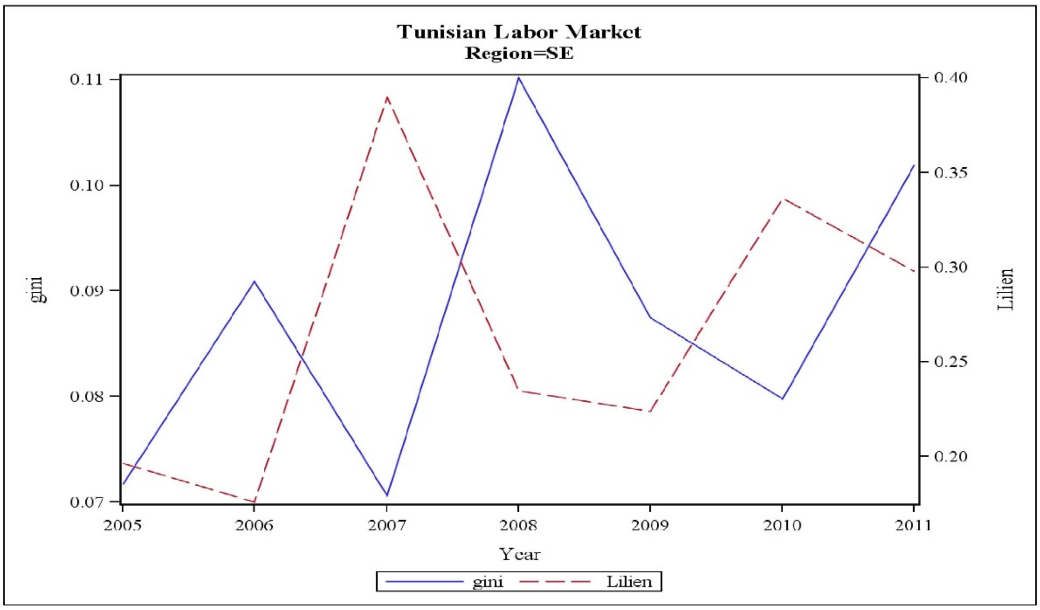

Figure 11: Lilien and Gini Indexes: Southwest

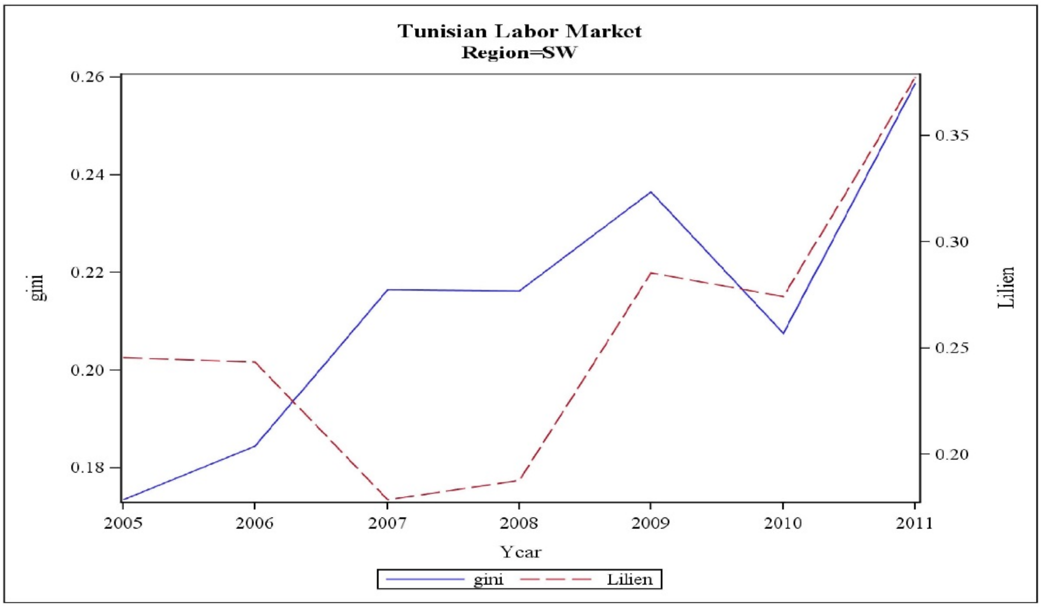

Figure 12: Unemployment Growth Rate (2005-11)

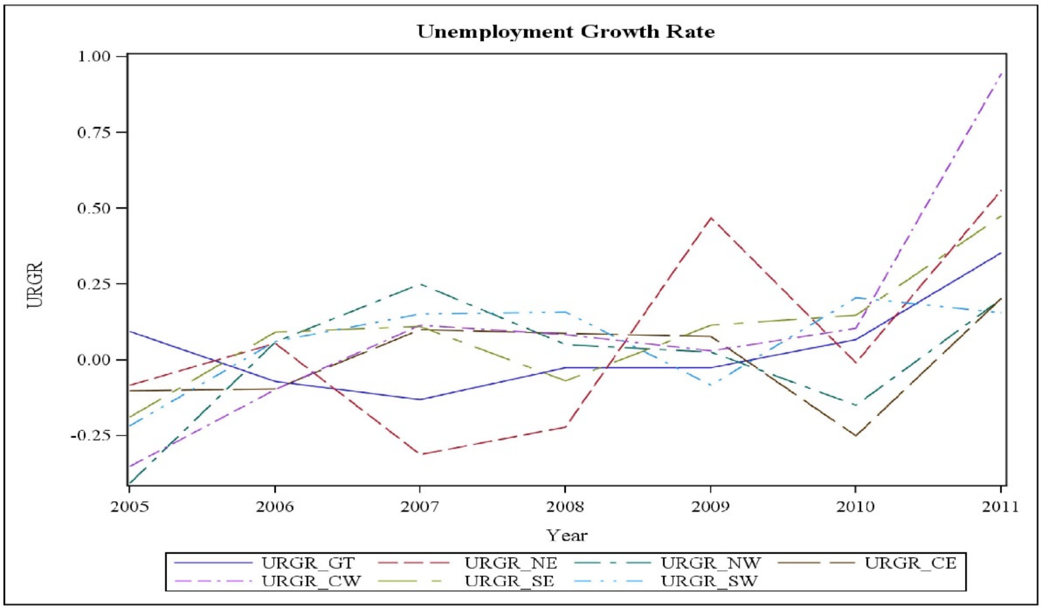

Figure 13: Supply-Demand Mismatch (2005-11)

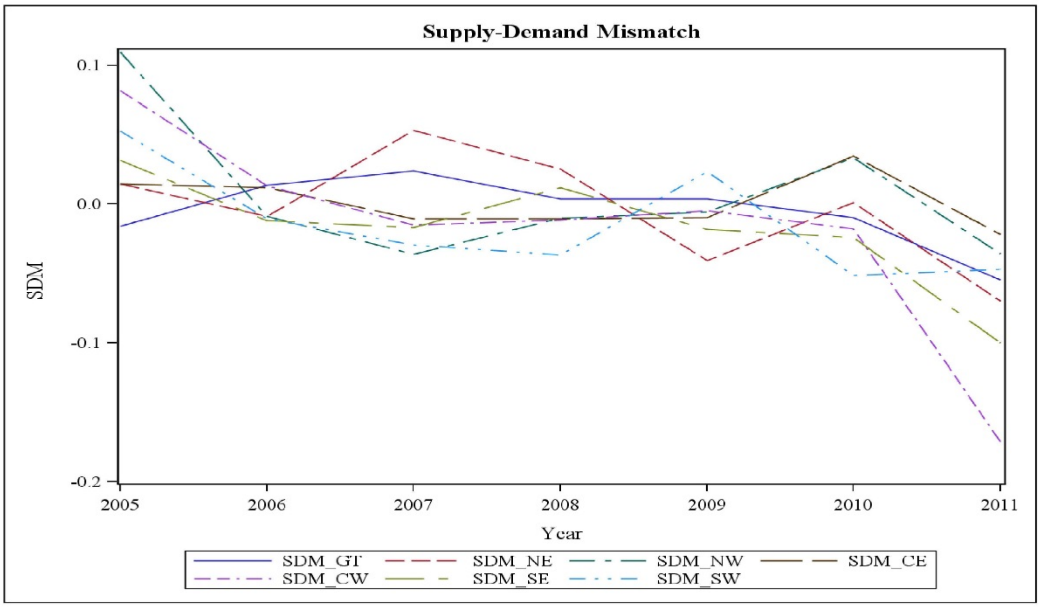

Figure 14: Cohort's Density Growth Rate (2005-11)

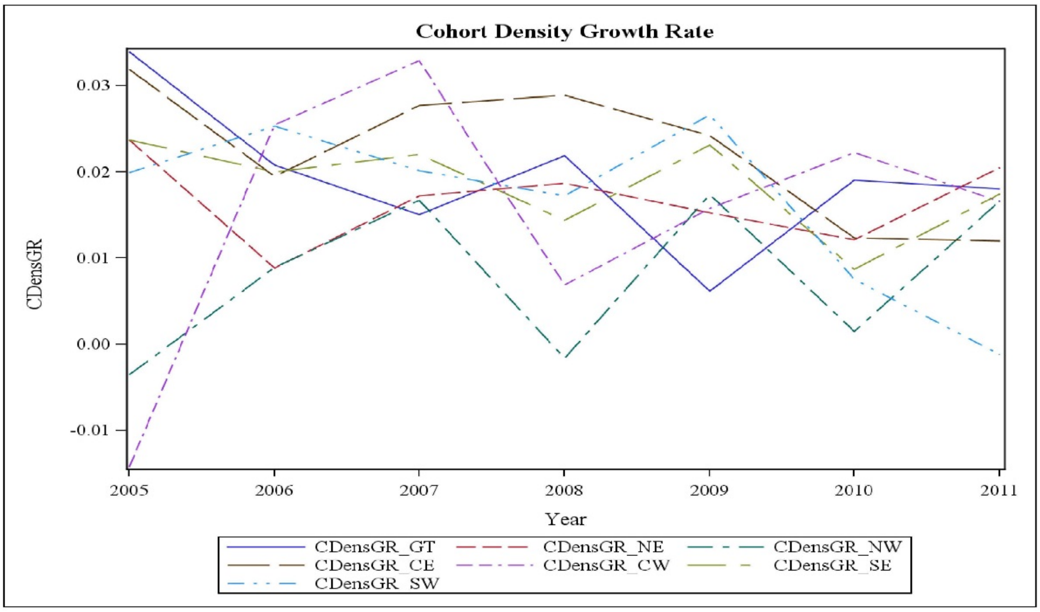

Figure 15: Regional Evolution of the Tunisian Labor Market (2005-11)

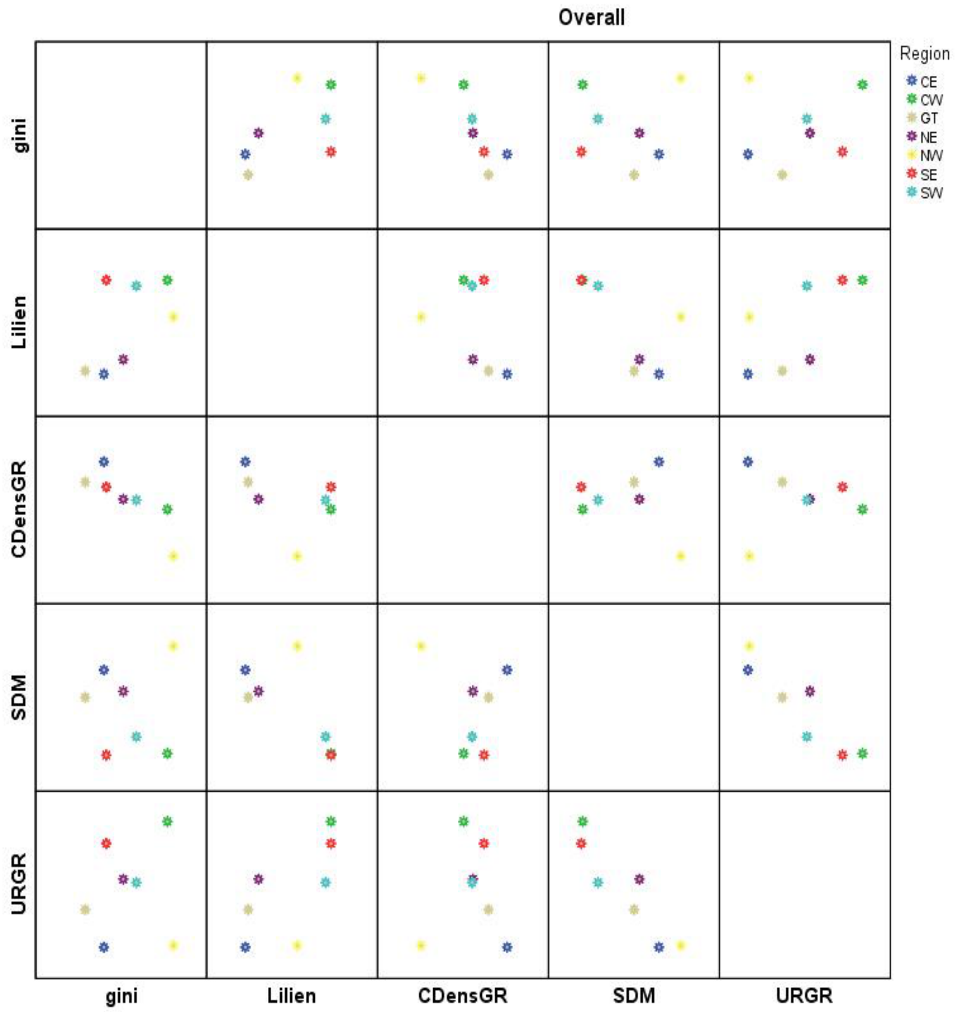

Figure 16: Regional Evolution of the Tunisian Labor Market: Cluster Analysis - Principal Component Analysis

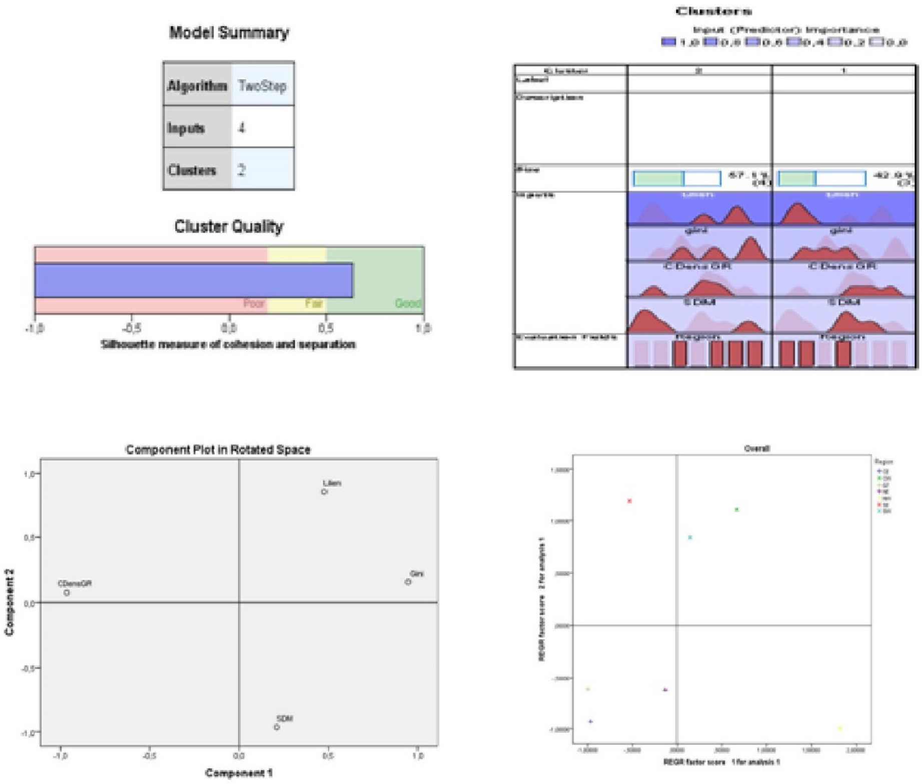

Figure 17: Regional Evolution of the Tunisian Labor Market: Pre-Revolution

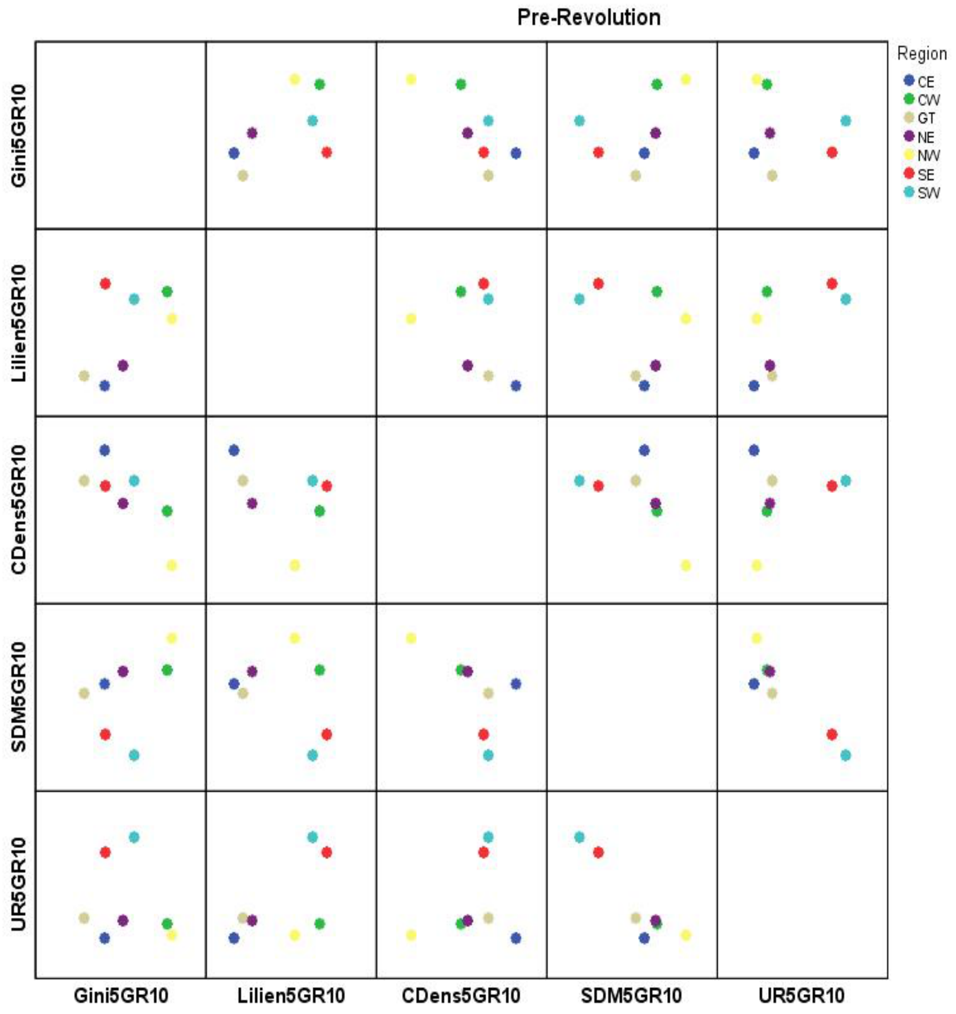

Figure 18: Regional Evolution of the Tunisian Labor Market: Post-Revolution

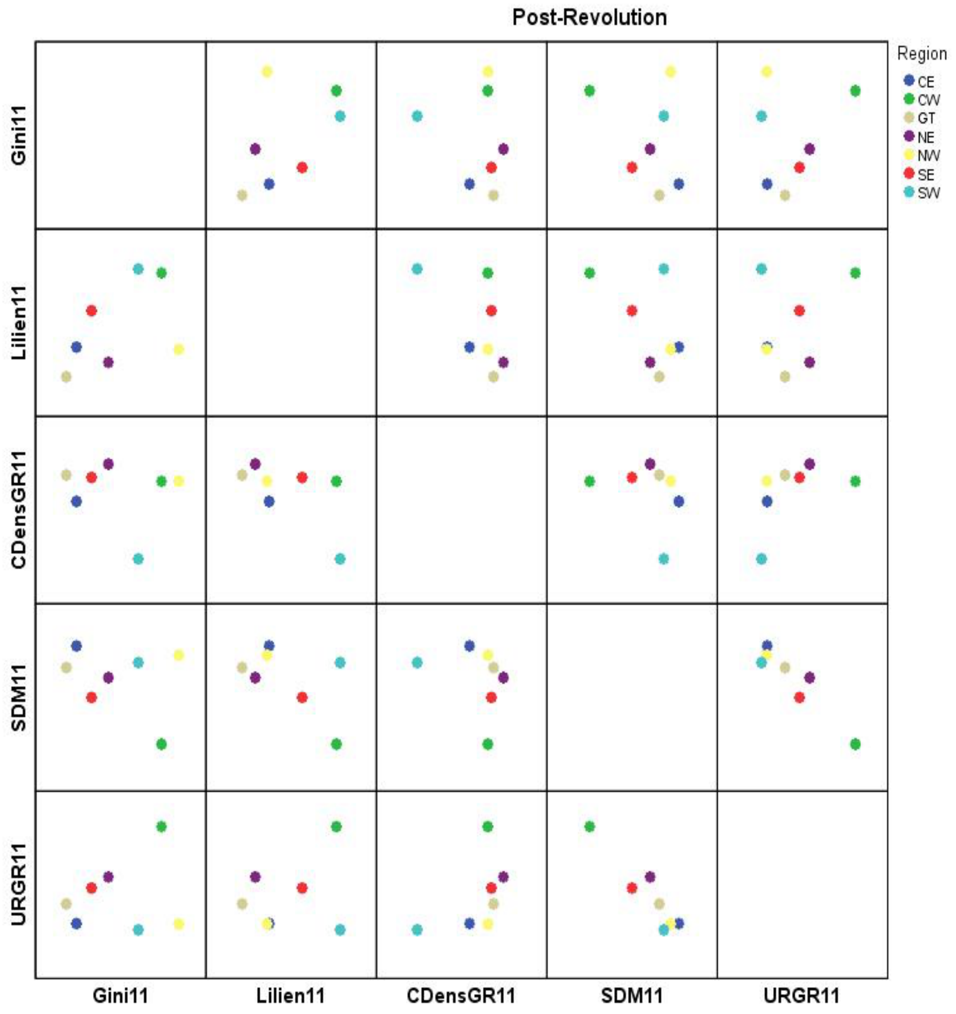

Figure 19: Regional Evolution of the Tunisian Labor Market in the Pre-Revolution: Cluster Analysis - Principal Component Analysis

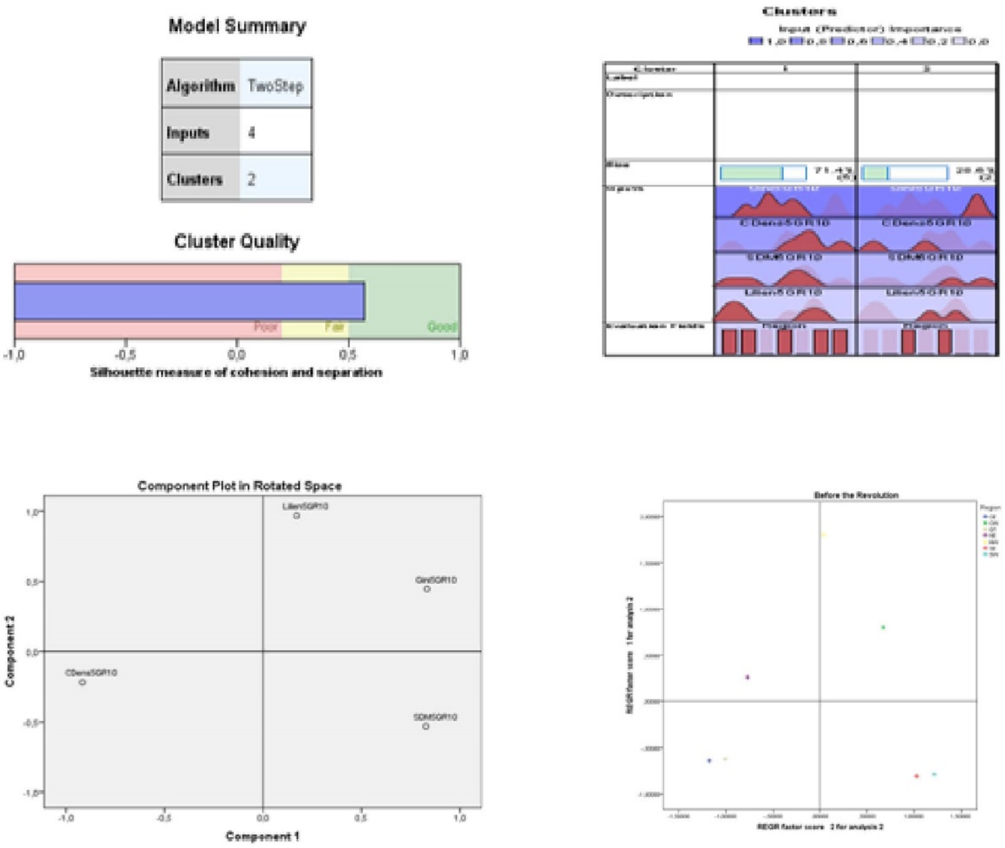

Figure 20: Regional Evolution of the Tunisian Labor Market in the Post-Revolution: Cluster Analysis - Principal Component Analysis

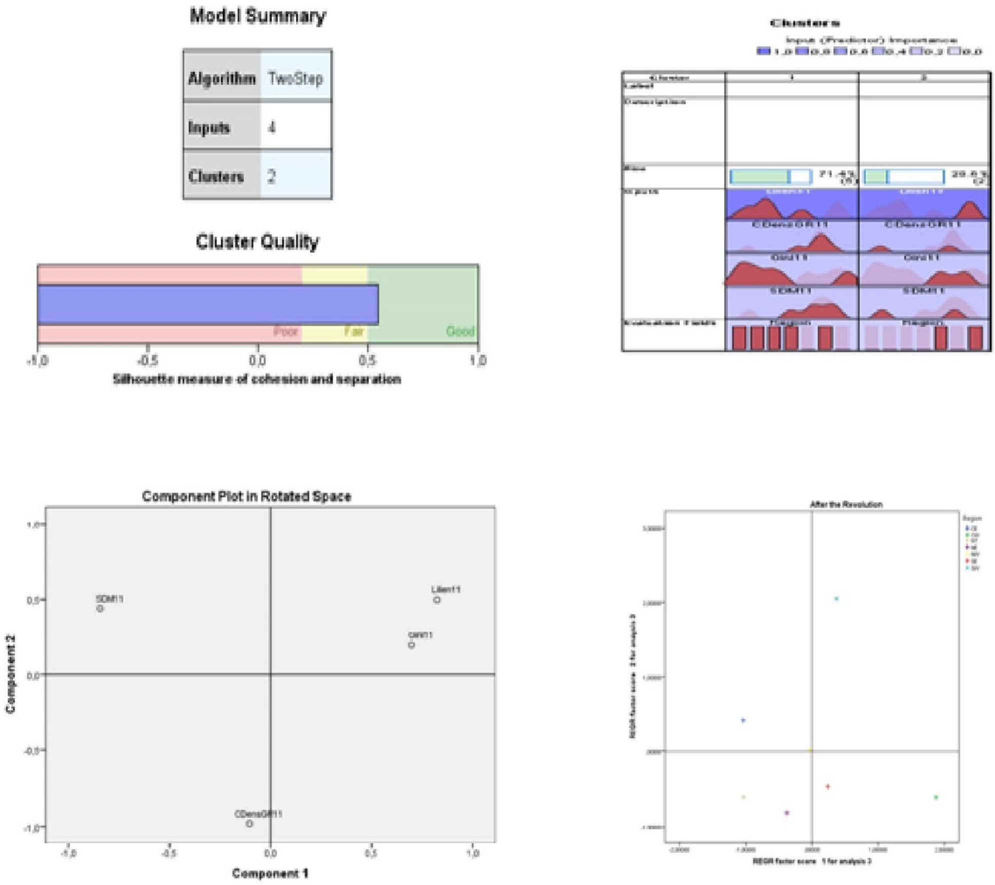

Figure 21: Conditional Path

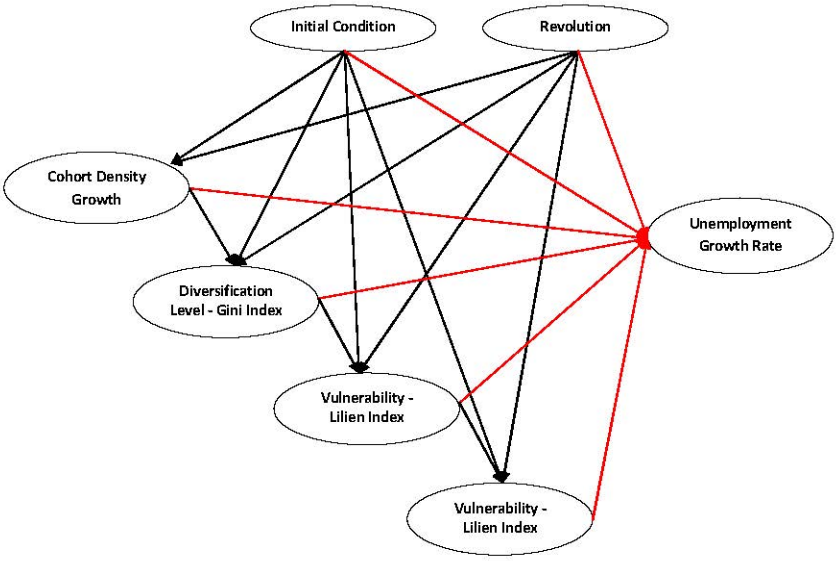

Table 1: Harris-Tzavalis Unit-Root Test

Variables	Statistic
URGR	0.0128***
SDM	0.0466***
Lilien	0.2064**
Gini	0.0783***
CDensGR	-0.1646***

Notes: * 10% significance level, ** 5% significance level, *** 1% significance level.

Table 2: Measures of Global Spatial Autocorrelation (Moran's I)

Variables	I	p-value †
URGR05	0.195	0.120
URGR06	-0.018	0.335
URGR07	0.344	0.038
URGR08	-0.051	0.343
URGR09	-0.427	0.096
URGR10	0.127	0.177
URGR11	-0.587	0.064

Notes: † 1-tail test

Table 3: Conditional Path

Variables	Importance rank	Conditional Path
CDensGR	1	
Gini	2	CDensGR
Lilien	3	CDensGR Gini
SDM	4	CDensGR Gini Lilien

Table 4: Geographic Weighted Regression

	URGR05		URGR06		URGR07		URGR08		URGR09		URGR10		URGR11	
	Coefficient	**Significance test for spatial non-stationarity**	**Coefficient**	**Significance test for spatial non-stationarity**	**Coefficient**	**Significance test for spatial non-stationarity**	**Coefficient**	**Significance test for spatial non-stationarity**	**Coefficient**	**Significance test for spatial non-stationarity**	**Coefficient**	**Significance test for spatial non-stationarity**	**Coefficient**	**Significance test for spatial non-stationarity**
CDensGR	-1.117	0.280	-0.546	0.500	0.825	0.590	0.009	0.990	3.861	0.830	2.339	0.900	27.137***	0.450
Gini	-1.028***	0.890	0.132*	0.870	0.001	0.710	0.171	1.000	-0.023	0.750	-0.100	0.550	0.560*	0.510
Lilien	-0.294	0.190	-0.206	0.500	-0.017	0.470	-0.302	0.960	-1.052	0.510	0.622**	0.610	0.726*	0.600
SDM	-4.119**	0.760	-6.873**	0.490	-6.029***	0.070	-6.179**	0.080	-9.046**	0.460	-5.230***	0.470	-5.100**	0.720
Adjusted R-squared	0.958		0.950		0.976		0.815		0.767		0.865		0.963	
Significance level for Bandwidth	0.670		1.000		1.000		0.130		0.000		1.000		0.300	
VIF - Collinearity	12.610		15.670		9.060		2.910		108.650		2.490		7.070	
VIF - Sequential Approach	2.530		1.080		4.160		1.260		1.010		1.060		1.610	

Notes: * 10% significance level, ** 5% significance level, ** 1% significance level

Table 5: Conditional Path

Variables Variables	Importance Rank	Conditional Path	
		Pre-Revolution	**Post-Revolution**
UR04/10	1		
CDensGR	2	UR04	UR10
Gini	3	UR04 CDensGR	UR10 CDensGR
Lilien	4	UR04 CDensGR Gini	UR10 CDensGR Gini
SDM	5	UR04 CDensGR Gini Lilien	UR10 CDensGR Gini Lilien

Table 6: Measures of Global Spatial Autocorrelation (Moran's I): Pre- vs. Post-Revolution

Variables	I	p-value †
UR5GR10	0.600	0.064
UR10GR11	-0.587	0.008

Notes: † 1 tail test

Table 7: Geographic Weighted Regression: Pre- vs. Post-Revolution

	Pre-Revolution UR05GR10		Post-Revolution UR10GR11	
	Coefficient	**Significance test for spatial non-stationarity**	**Coefficient**	**Significance test for spatial non-stationarity**
UR04	-0.0002	0.811		
UR10			0.02478***	0.695
CDensGR	0.3858	0.370	20.7422**	0.121
Gini	-0.1187	0.483	0.4362	0.296
Lilien	0.4547**	0.090	2.9036*	0.923
SDM	-3.8752**	0.086	-4.5562*	0.489
Adjusted R-squared	0.930		0.959	
VIF - Collinearity	25.080		18.140	
VIF - Sequential Approach	1.090		1.030	

Notes: * 10% significance level, ** 5% significance level, *** 1% significance level

Table 8: The Farrar-Glauber Multicollinearity Tests

X^2-test	P-value > X^2_{15}
103.583	0.0000
Variables	F **-test (** $F_{43,5}$ **)**
Revolution	8.087**
LUR04	21.363***
CDensGR	3.282*
Gini	19.529***
Lilien	3.190*
SDM	7.436**

Notes: *10% significance level, ** 5% significance level, *** 1% significance level

Table 9: The Farrar-Glauber Multicollinearity t-test

	LUR04	SDM	CDensGR	Gini	Lilien	Revolution
LUR04						
SDM	-0.145					
CDensGR	-2.654	-1.338				
Gini	9.706	0.056	-2.685			
Lilien	2.963	-0.835	-1.784	2.672		
Revolution	0.000	-5.064	-0.659	0.207	2.057	

Table 10: Conditional Path

Variables	Importance rank	Conditional Path
LUR04	1	
Revolution	1	
CDensGR	2	LUR04 Revolution
Gini	3	LUR04 Revolution CDensGR
Lilien	4	LUR04 Revolution CDensGR Gini
SDM	5	LUR04 Revolution CDensGR Gini Lilien

Table 11: Conditional Path: Coefficients

	CDensGR	Gini	Lilien	SDM
LUR04	0.0059***	0.0657***	0.0677***	0.0012
Revolution	-0.0025	0.0116*	0.0801***	-0.0739***
CDensGR		-0.2841	-1.3702	-0.9466**
Gini			0.1571	-0.0323
Lilien				-0.0981***

Notes: * 10% significance level, ** 5% significance level, *** 1% significance level

Table 12: Panel Data Non Normality and Heteroscedasticity Tests

Panel Data Non Normality Tests	
Anderson-Darling	P-value > $Z(3.070)$
.4355	0.9989
Jarque-Bera	P-Value > χ^2_2
.6034	0.7396
White IM	P-Value > χ^2_2
.4137	0.1814
Panel Data Heteroscedasticity Tests	
Hall-Pagan Tests	P-value > χ^2_1
$E2 = Yh$	0.1525
$E2 = Yh2$	0.1273
$E2 = LYh2$	0.0308
Likelihood Ratio Test å	P-value > χ^2_7
.51	0.0000
Engle LM ARCH Test AR(1)	P-value > χ^2_1)
$E2 = E2_1$	0.0008
Greene Likelihood Ratio Tests	
Variables	P-value > χ^2_6
LUR04	0.00194
CDensGR	0.05551
Gini	0.00000
Lilien	0.05204
SDM	0.02283
URGR	0.10810

Notes: * Assumption: homoskedastic nested in heteroskedastic.

Table 13: MLE Random-Effects Panel Data Regression: Spatial Durbin Model (LeSage and Pace, 2009)

		Coefficient	Wx	Direct Effect	Indirect Effect	Total Effect
Constant		-0.0529829				
URGR L1.		-.047107				
Revolution		0.1137804***		0.1223603***	0.0259983***	0.1483586***
LUR04		0.0201428	-0.0011246***	0.0183271	-0.0057825	0.0125447
CDensGR		2.095532***	-0.5257522***	0.6632545	-4.563348**	-3.900093*
Gini		0.0172345	-0.0131876**	-0.0191739	-0.1213897	-.0.1405636
Lilien		0.1207246**	-0.0422063***	0.0060582	-0.3746692***	-0.368611*
SDM		-1.620363***	0.1097226***	-1.401489***	0.6872829**	-0.7142058
Spatial Rho					0.0241748***	
AIC					-165.4186	
BIC					-137.6159	
R-Squared			Whitin		0.8964	
			Between		0.9584	
			Overall		0.8985	
Hausman tests	Random Effects vs. Fixed Effects		Time		122.43***	
			Individuals		182.79***	
			Both		251.00***	
Test for SAR			χ_6^2		30.83***	
Test for SEM			χ_6^2		19. 26***	
SAC			Overall R-Squared		0.3799	
Jarque-Bera Non Normality LM Test			χ_2^2		5. 95419*	
Greene Likelihood Ratio Panel Heteroscedasticity Test			χ_6^2		24.37427***	
Breusch-Pagan Lagrange Multiplier Panel Heteroscedasticity Test			χ_6^2		26.85834***	
Panel Groupwise Heteroscedasticity Tests	Lagrange Multiplier LM Test		χ_6^2		26.8583***	
	Likelihood Ratio LR Test		χ_6^2		24.3743***	
	Wald Test		χ_7^2		97.4533***	

Notes: * 10% significance level, ** 5% significance level, *** 1% significance level

Table 14: MLE Random-Effects Panel Data Regression: Spatial Durbin Panel Multiplicative Heteroscedasticity Model (Log-Log)

		Coefficient	Elasticity	Marginal Effect	Mean
Constant		-3.048559			
Revolution		-0.8254932	-0.8255	-0.0772	0.1429
LUR04 †		0.9969675	0.9970	0.0048	2.7848
CDensGR		0.0756299	0.0756	3.1787	0.0003
Gini		0.2718673	0.2719	-0.5771	-0.0063
Lilien		-0.0037177	-0.0037	0.1505	-0.0003
SDM		-.0.4676538***	-0.4677	-43.4606	0.0001
Wx.LUR04		0.1130123	0.1130	0.0001	11.1000
Wx.CDensGR		0.0334283**	0.0334	-0.0000	-32.0675
Wx.Gini		0.0888407**	0.0888	-0.0001	-9.9712
Wx.Lilien		0.0014837	-0.0243	0.0000	-16.7787
Wx.SDM		-0.0063616	-0.0064	0.0000	-20.8154
Spatial Rho				7.571346***	
AIC				2.3870	
SC				4.4272	
R-Squared				0.7999	
Adjusted R-Squared				0.6902	
Wald Test			χ^2_{11}	41.4496***	
Jarque-Bera Non Normality LM Test			χ^2_2	0.6844	
Panel Heteroscedasticity Tests	Engle LM ARCH Test AR(1)		χ^2_1	0.0675	
Panel Groupwise Heteroscedasticity Tests	LM Test		χ^2_6	6.0560	
	LR Test		χ^2_6	6.3810	
	Wald Test		χ^2_7	12.2540	

Notes: † Multiplicative Heteroscedasticity Variable. * 10% significance level. ** 5% significance level, *** 1% significance level