Volatility and regional growth in Europe: Does space matter?

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Abstract

This paper investigates the relationship between volatility and economic growth in the European regions over the period 1995-2008. To that end, we estimate a two-way fixed effects panel data model using spatial econometric techniques that allow us to incorporate into the analysis the relevance of spatial effects in the processes of regional growth in Europe. The results show the existence of a positive and statistically significant relationship between the fluctuations of the business cycle and regional growth, which is mainly consequence of the spatial spillovers induced by the incidence of volatility in neighbouring regions. This finding is robust to the inclusion in the analysis of different explanatory variables that may affect regional growth such as the initial GDP per capita, the level of investment or industry mix. Furthermore, the results of the paper do not depend on the specific measure of volatility used, or the spatial weights matrix employed to capture the degree of spatial interdependence between the sample regions. The observed relationship suggests that traditional stabilization policies that attempt to reduce the fluctuations of the business cycle may be harmful for economic growth in the European regions.

Keywords: Volatility, growth, spatial effects, regions, Europe.

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1 Introduction

Over the last two decades there have been numerous studies on spatial disparities in Europe using a variety of different approaches and methods. This increasing interest has to do with the important advances that have taken place in economic growth theory, coinciding with the introduction of endogenous growth models in the mid 1980s (Barro and Sala-i-Martin, 1995). The assumptions underlying these models ultimately allow for the reversal of the neoclassical prediction of convergence, and lead to the conclusion that the faster growth of rich economies leads to increase regional disparities. In fact, the self-sustained and spatially selective nature of economic growth is also highlighted by many models of the "new economic geography" developed since the seminal contribution by Krugman (1991). According to these theories, increasing returns and agglomeration economies explain the accumulation of economic activity in the more dynamic areas, which causes ultimately spatial divergence. Academic debate aside, however, the increasing relevance of this topic in the European setting is closely related to the strong emphasis placed on achieving economic and social cohesion in the context of the process of integration currently underway (European Commission, 2007).

The literature has stressed the role played by various factors on regional growth in Europe. They include the sectoral composition of economic activity (Paci and Pigliaru, 1999), structural change processes (Gil et al., 2002), technology and innovation capacity (Fagerberg et al., 1997), human capital stock (Rodríguez-Pose and Vilalta-Bufi, 2005), infrastructure endowment and investment (Crescenzi and Rodríguez-Pose, 2008), European regional policy (Rodríguez-Pose and Fratesi, 2004), social capital (Beugelsdijk and Van Schaik, 2005), or income distribution (Ezcurra, 2009). Nevertheless, the study of the possible relationship between volatility and regional growth has received hardly any attention in this context. Indeed, to the best of our knowledge, only Martin and Rogers (2000) and Falk and Sinabell (2009) have examined this issue in a sample of European regions using aggregate data for the economy as a whole. Martin and Rogers (2000) identify a negative relationship between volatility and growth in a sample of 90 NUTS-1 and NUTS-2 regions during the period 1979-1992.[1] This finding contrasts with the positive correlation observed by Falk and Sinabell (2009) in 1,084 NUTS-3 regions between 1995 and 2004.[2]

The limited number of analysis on the volatility-growth connection in the European setting is especially remarkable in view of the abundant theoretical arguments supporting the existence of a link between short-term economic instability and economic performance (Ramey and Ramey, 1995; Aghion and Howitt, 1998). Moreover, the issue poses potentially important implications for the design of policy (Norrbin and Pinar Yigit, 2005). In particular, the presence of a positive relationship suggests that public policies that endeavour to reduce the variability of cyclical macroeconomic fluctuations may restrict the possibilities of growth in the long-term. On the contrary, the existence of a negative link implies that the government policies designed to stabilize the business cycle will help to rise the long-term growth rate of the economy.

Against this background, and in order to complete the results obtained so far in the existing literature, this paper aims to examine further the relationship between volatility and regional growth in Europe. In particular, our study pays specific at-

[1] NUTS is the French acronym for "Nomenclature of Territorial Units for Statistics", a hierarchical classification of subnational spatial units established by Eurostat according to administrative criteria. In this classification, NUTS-0 corresponds to the country level, while increasing numbers indicate increasing levels of territorial disaggregation.

[2] In addition to these contributions based on aggragate data, Ezcurra (2010) employs sectorally dissagregated data for six manufacturing activities to investigate the relationship between the fluctuations of the business cycle and output growth in the European regions between 1980 and 2006.

tention to the underlying geographical dimension of the processes of regional growth in the European setting. Accordingly, the sample regions are not treated as isolated units that evolve independently of the rest, and spatial effects are incorporated formally into the analysis. This approach allows us to investigate the role played by spatial spillovers in explaining the impact of volatility on regional growth in Europe.

The paper distinguishes itself from the earlier studies by Martin and Rogers (2000) and Falk and Sinabell (2009) mentioned above in three major aspects. First, there are important differences from a methodological perspective. Martin and Rogers (2000) and Falk and Sinabell (2009) use cross-sectional data to investigate the relationship between volatility and economic growth in the European regions, whereas our analysis is based on panel data. The employment of panel data leads usually to a greater availability of degrees of freedom, thus reducing the collinearity among explanatory variables and improving the efficiency of the estimates (Baltagi, 2001; Hsiao, 2003). Panel data also allow us to take into account unobserved heterogeneity (Islam, 2003). This is particularly useful in our context, since region-specific factors are likely to affect regional growth patterns. Second, unlike the present paper, Martin and Rogers (2000) and Falk and Sinabell (2009) do not add the investment level as a control variable when estimating the relationship between volatility and economic growth in the European regions. This omission may affect their findings, since there are numerous theoretical arguments that suggest the relevance of investment in this context (Pindyck, 1991; Aizenman and Marion, 1993). Third, the sample used in our analysis includes a total of 29 European countries. This means that the country coverage is considerably greater than in the previous studies by Martin and Rogers (2000) and Falk and Sinabell (2009).

The paper is organized as follows. After this introduction, section 2 reviews briefly several of the theoretical arguments proposed in the literature to justify the possible connection between the variability of cyclical macroeconomic fluctuations and economic performance, as well as the main results obtained so far in the empirical research on this topic. Section 3 gives details of the dataset used in the study and provides some preliminary evidence on the volatility-growth link in the European regions. Section 4 describes the econometric approach used in our analysis. The main findings of the paper are presented in section 5. The final section offers the main conclusions from our work and the policy implications of the research.

2 The relationship between volatility and economic growth in the literature

Business cycle fluctuations and long-run growth have traditionally been treated by economists as separate areas of research. According to this perspective, the long-term growth rate of the economy was considered as an exogenous trend that was not affected by short-term shocks. This point of view, however, has been questioned over the last three decades, coinciding with the publication of various contributions that link both phenomena in a common theoretical framework (e.g. Kydland and Prescott, 1982; Long and Plosser, 1983; Aghion and Saint-Paul, 1998).

From a theoretical perspective, there are several arguments to believe that volatility and economic growth may be related, either positively or negatively (Aghion and Howitt, 1998; Manuelli and Jones, 2005). Thus, Schumpeter (1939) points out that the variability of the cyclical macroeconomic fluctuations contributes to improve the degree of efficiency of the economic system as a whole, thus increasing the long-term growth rate. Following this idea, various authors stress the association between the opportunity cost of accumulation of organizational capital or the investment in productivity-enhancing activities, and the fluctuations of the business cycle (e.g. Saint-Paul, 1993). A similar result can be due to the presence of precautionary saving (Mirman, 1971), or investment processes with symmetric adjustment costs (Hartman, 1972). In this situation, higher volatility should lead to a higher saving rate, and therefore a higher investment rate. Consequently, higher volatility would enhance economic growth. In turn, Black (1987) suggests that economies may have to choose between low-variance, low-expected-returns technologies, and high-variance, high-expected returns technologies. Following this idea, Acemoglu and Zilibotti (1997) develop a model where the choice between technologies with different levels of risk gives rise to different growth patterns. In this setting, those economies with greater fluctuations in economic activity would be characterized by greater growth rates.

Nevertheless, there are also several reasons supporting a negative relationship between volatility and economic growth. In particular, the existence of irreversibilities in investment (i.e. asymmetric adjustment costs) may imply that higher volatility is associated with lower investment levels (Bernanke, 1983; Pindyck, 1991). Another possible explanation for a negative link between short-term instability and economic performance is suggested by Ramey and Ramey (1991). According to these authors, if firms have to select the technology used in advance, then the uncertainty of returns that exists when volatility is high may hamper economic growth. Similarly, Martin and Rogers (2000) propose a model where learning by doing is at the origin of the long-run growth, which predicts a negative relationship between volatility and growth.

The different arguments laid down above show that the link between the variability of cyclical macroeconomic fluctuations and economic performance is theoretically ambiguous, as volatility can affect growth via several different mechanisms that often work in opposite directions. Consequently, empirical research has attempted to shed light on the relationship between volatility and growth. In fact, numerous papers have explored this issue during the last years using cross-country data and different econometric techniques. Some authors find support for a positive link between volatility and growth (e.g. Kormendi and Meguire, 1985; Grier and Tullock, 1989; Caporale and McKiernan, 1996), while other researchers report a negative correlation (e.g. Ramey and Ramey, 1995; Martin and Rogers, 2000; Norrbin and Pinar Yigit, 2005). Finally, there are papers where the observed link is not statistically significant (e.g. Speight, 1999; Chatterjee and Shukayev, 2006).

Taking into account the problems involved with systematic data quality variations that affect many cross-country analyses, several scholars have investigated this issue using regional data from the US (Chatterjee and Shukayev, 2006; Dawson and Stephenson, 1997), Canada (Dejuan and Gurr, 2004), or the EU (Martin and Rogers, 2000; Falk and Sinabell, 2009). The regional approach is particularly appealing in this context, as the use of smaller geographical areas allows the researcher to increase the number of observations employed in the econometric analysis (Falk and Sinabell, 2009). In any case, the empirical work on the relationship between volatility and economic growth based on regional data has been so far limited and, as occurs with cross-country studies, generally reaches diverging conclusions. As can be observed in Table 1, available empirical analyses at the regional level virtually fit every possible position. The reasons for this diversity of results have to do with the fact that these contributions differ considerably in terms of the sample composition and the study period, the indicator used to measure the degree of volatility, and the econometric approach. As a consequence, the question of whether the fluctuations of the business cycle have a positive or negative impact on regional growth is far from settled and further empirical research is required.

INSERT TABLE 1 AROUND HERE

3 Data and preliminary evidence

As mentioned in the introduction, this paper aims to examine empirically the relationship between volatility and economic growth in the European regions. The data for this study are drawn from the Cambridge Econometrics regional database. The sample covers a total of 279 NUTS-2 regions belonging to the 27 EU member states, as well as Norway and Switzerland. In order to maximize the number of regions included in the analysis, the study period goes from 1995 to 2008.[3] NUTS-2 regions are used in the analysis instead of other possible alternatives for various reasons. First, NUTS-2 is the territorial unit most commonly employed in the literature to investigate the determinants of regional growth in Europe, which facilitates the comparison of our results with those obtained in previous papers. Second, NUTS-2 regions are particularly relevant in terms of EU regional policy since the 1989 reform of the European Structural Funds.

The key variables throughout the paper are the average and the standard deviation

[3] The lack of complete series has obliged us to exclude from the study the French overseas departments and territories, and the Portuguese islands in the Atlantic.

of the growth rates of real GDP per capita in the various regions between 1995 and 2008. The average annual growth rate for the Eurpean regions as a whole is 2.13%, and the standard deviation of growth is 2.14 on average. Nevertheless, both variables exhibit a high degree of variation across the sample regions during the study period. Thus, there are fast growing regions with important fluctuations in economic activity, as in the cases of the Irish regions, Algarve in Portugal, Attiki in Grece or Aland in Finland. Likewise, high levels of volatility are also found in some regions with low growth rates, as occurs with Liguria or Calabria in Italy, Champagne-Ardenne in France or Sterea Ellada in Greece. This is not particularly surprising given the heterogeneous behaviour in terms of economic performance experienced by the sample regions during the study period, which gives a clear indication of the complexity of regional growth patterns in Europe (Rodríguez-Pose, 2002).

Our empirical research begins with a preliminary analysis on the relationship between volatility and regional growth. To this end, the various regions are divided into two and three groups according to their average level of volatility between 1995 and 2008. The definition of the different groups is based on the median (classification into two groups), and the first and third quartile (classification into three groups) of the distribution of the standard deviation of GDP per capita regional growth rates. As can be seen in Table 2, more volatile regions tend to register on average greater growth rates. By contrast, those regions with less volatility are characterized in general by lower growth rates. This is corroborated by the corresponding F-tests, which show that the differences between the groups in terms of the average growth rate are statistically significant at the 1% level.

INSERT TABLE 2 AROUND HERE

However, when interpreting the information provided by Table 2, it should be noted that the results discussed above may be ultimately sensitive to the specific number of groups used to classify the various regions. Bearing this in mind, Figure 1 plots the average growth rate of the sample regions on its standard deviation. The scatter plot suggests the existence of a positive link between volatility and regional growth in Europe. In fact, the relationship is statistically significant (t-value is 3.49), which is consistent with the information provided by Table 2.

INSERT FIGURE 1 AROUND HERE

4 Econometric approach

The previous analysis allows us to obtain some first insights on the link between volatility and economic growth in the European regions. Nevertheless, the information provided by Table 2 and Figure 1 should be cautiously interpreted because omitted variables could ultimately cause the observed relationship. In this respect, it is likely that the growth rate registered by the sample regions during the study period does not depend only on the fluctuations of the business cycle. Furthermore, the preliminary evidence presented above is based exclusively on the study period as a whole, which is consistent with the cross-sectional approach used in previous studies on the volatility-growth connection in the European regions (Martin and Rogers, 2000; Falk and Sinabell, 2009). Nevertheless, the nature of our dataset allows us to employ panel data techniques in this context, thus extending modelling possibilities as compared to the single equation cross-sectional setting employed so far (Baltagi, 2001; Hsiao, 2003). In particular, we begin by considering in our empirical analysis the following two-way fixed effects model:[4]

$$\Delta Y_{it} = \alpha + X_{it}\beta + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where ΔY is the average growth rate of GDP per capita in region i measured over five-year periods, X is a vector that includes the measure of volatility defined above, as well as a set of additional variables that control for other factors that are assumed to influence regional growth.[5] In turn, μ denotes unobservable region-specific effects and λ time-specific effects common to all regions. Finally, ε represents the corresponding disturbance term.

The control variables included in vector X have been selected on the basis of the findings of existing studies on the determinants of regional growth in Europe. While the choice of these variables is theoretically well grounded, it ultimately depends on the availability of reliable statistical data for the geographical setting on which our study is focused. Thus, following the convention in the literature on economic growth, the initial level of GDP per capita is used to control for economic convergence across regions (Barro and Sala-i-Martin, 1991, 1992). The inclusion of this variable in the model allows us to determine whether poor regions grew faster than richer ones during the study period, thus providing information on the dynamics of regional disparities. We also control for the investment level and the population growth rate of the sample

[4]As an alternative, we also considered the estimation of a random effects model. Nevertheless, the different Hausman tests carried out reject in all cases the appropriateness of the random effects model in this context.

[5]As is usual in the literature, the dependent variable of the model is the regional growth rate averaged over five year periods (e.g. Ramey and Ramey, 1995). Nevertheless, as a robustness test, we checked that the main results of the paper are not affected whether we employ alternatively the growth rates measured over ten-year periods. Further details are available upon request.

regions, two variables theoretically important when it comes to explaining capital accumulation and economic growth (Mankiw et al., 1992; Barro and Sala-i-Martin, 1995).

Additionally, regional growth patterns may be affected by the possible existence of agglomeration economies (Ciccone, 2002; Fujita and Thisse, 2002). Agglomeration economies result from market and non-market interactions, and imply that proximity to larger markets leads to productivity gains. In order to capture the degree of spatial concentration of economic activity in a given area, we add to the list of regressors of our baseline model the employment density of the various regions (Ciccone, 2002). Furthermore, the economic performance of the sample regions may be related to the sectoral composition of economic activity. Indeed, numerous studies have found that industry mix affects regional growth in the EU (Paci and Pigliaru, 1999). Although the European economy have experienced a process of convergence in regional productive structures during the last decades, considerable differences persist in the patterns of regional specialization across Europe (Ezcurra et al., 2006). Accordingly, vector X also includes the regional employment shares in agriculture, financial services and non-market services.

At this point it is important to note that, as is usual in the traditional convergence literature, equation (1) considers the various regions as isolated units, thus ignoring the spatial characteristics of the data and the potential role of geography in shaping economic growth (Rey and Janikas, 2005). This should raise no major problems, as long as each economy evolves independently of the rest. However, this does not seem a very realistic assumption in the context of the economic integration process currently underway in Europe. On the contrary, the importance of interregional trade, migratory movements and technology and knowledge transfer processes suggests that geographical location may play an important role in explaining regional growth patterns in the European setting (Magrini, 2004; Creszenci, 2005; Fingleton and López-Bazo, 2006). Nevertheless, the consequences of omitting these spatial effects from the specification of equation (1) are potentially important from an econometric perspective, and may cause estimates to become biased, inconsistent and/or inefficient (Anselin, 1988; Anselin and Bera, 1998). Accordingly, we should take into account this potential problem in our empirical analysis. Nevertheless, we have no a priori spatial specification model in mind. For this reason, we begin by considering a two-way fixed effects spatial Durbin model, which is sufficiently general to allow for different types of spatial interactions between the sample regions. This model can be written as follows:

$$\Delta Y_{it} = \alpha + \rho W \Delta Y_{it} + X_{it}\beta + W X_{it}\theta + \mu_i + \lambda_t + \upsilon_{it} \tag{2}$$

where W is the spatial weights matrix used to capture the degree of spatial interdependence between the various regions, and υ is the disturbance term. As can be observed, in this specification the regional growth rates depend on the spatial lag of the dependent variable, WΔY, which captures the spatial effects working through the dependent variable. In addition, the model also includes the spatial lag of the measure of volatility and of the rest of control variables, WX.

The presence of spatial lags of the explanatory and dependent variables complicates the interpretation of the parameters in equation (2) (Le Gallo et al., 2003; Anselin and Le Gallo, 2006). Therefore, some caution is required when interpreting the estimated coefficients in the spatial Durbin model. As shown by LeSage and Pace (2009, pp. 33-42), in a spatial Durbin model a change in a particular explanatory variable in region i

has a *direct* effect on that region, but also an *indirect* effect on the remaining regions. In our context, the direct effect captures the average change in the economic growth rate of a particular region caused by a one unit change in that region's explanatory variable. In turn, the indirect effect can be interpreted as the aggregate impact on the growth rate of a specific region of the change in an explanatory variable in all other regions, or alternatively as the impact of changing an explanatory variable in a particular region on the growth rates of the remaining regions. Le Sage and Pace (2009) show that the numerical magnitudes of these two calculations of the indirect effect are identical due to symmetries in computation. Finally, the *total* effect is the sum of the direct and indirect impacts.

The specification in equation (2) is particularly useful in our context, because the spatial Durbin model allows one to estimate consistently the effect of volatility on regional growth when endogeneity is induced by the omission of a (spatially autoregressive) variable. Indeed, Le Sage and Pace (2009) show that if an unobserved or unknown but relevant variable following a first-order autoregressive process is omitted from the model, the spatial Durbin model produces unbiased coefficient estimates. Additionally, this model does not impose prior restrictions on the magnitude of potential spillovers effects. Furthermore, the spatial Durbin model is an attractive starting point for spatial econometric modelling because it includes as special cases two alternative specifications widely used in the literature: the spatial lag model and the spatial error model. As can be checked, the spatial Durbin model can be simplified to the spatial lag model when $\theta = 0$:

$$\Delta Y_{it} = \alpha + \rho W \Delta Y_{it} + X_{it}\beta + \mu_i + \lambda_t + \upsilon_{it} \tag{3}$$

and to the spatial error model if $\theta + \rho\beta = 0$:

$$\Delta Y_{it} = \alpha + X_{it}\beta + \mu_i + \lambda_t + \epsilon_{it} \tag{4}$$

where $\epsilon_{it} = \xi W \epsilon_{it} + \upsilon_{it}$ and $\upsilon_{it} \sim i.i.d.$

In any case, the spatial Durbin model produces unbiased coefficient estimates even when the true data-generation process is a spatial lag or a spatial error model.

The estimation of the various spatial models described above requires to define previously a spatial weights matrix. To do so, a first option is to use the concept of first order contiguity, according to which $w_{ij} = 1$ if regions i and j are physically adjacent and 0 otherwise. However, the use of this type of matrix may raise problems in the European context, given that the presence of islands means that W will include rows and columns containing only zeros. This implies that the observations in question are not considered in the analysis, which in turn has a potentially important effect on the interpretation of the results obtained. Taking this into account, the spatial weights matrix used in our analysis is defined as follows:

$$W = \begin{cases} w_{ij} = 0 \quad if \quad i = j \\ w_{ij} = \frac{1/d_{ij}^2}{\sum\limits_j 1/d_{ij}^2} \quad if \quad i \neq j \end{cases}$$

where d_{ij} is the great circle distance between the centroids of regions i and j. Note that this spatial weights matrix is based on the geographical distance between the various regions, which in itself is strictly exogenous. This is consistent with the recommendation of Anselin and Bera (1998) and allows us to avoid the identification problems raised by Manski (1993). As is usual in the literature, we use the inverse of the squared distance in order to reflect a gravity function. As can be observed, W is row standardized, so that it is relative, and not absolute, distance which matters.

5 Results

The first column of Table 3 presents the results obtained when the two-way fixed effects model described in equation (1) is estimated by OLS assuming that the disturbances are independent and identically distributed. As can be observed, the coefficient of the standard deviation of regional growth rates is positive and statistically significant at the 10% level. This seems to indicate the existence of a positive relationship between volatility and economic growth in the European regions, which is in line with the preliminary evidence provided by Table 2 and Figure 1. In addition, our results show that the coefficient of initial GDP per capita is negative and statistically significant, indicating the existence of a process of conditional convergence across the sample regions. Likewise, the remaining control variables included in vector X are in all cases statistically significant and have the expected signs.

INSERT TABLE 3 AROUND HERE

It should be recalled, however, that, as mentioned above, there are important reasons to believe that spatial effects play an important role in explaining regional growth patterns in the European setting. For this reason, we now proceed to calculate the Moran's I test to detect any potential spatial autocorrelation in the regional growth rates registered by the sample regions during the study period. Table 4 shows that the statistic is positive and statistically significant, which confirms the existence of a pattern of positive spatial association in this context.[6] This indicates that the European regions are likely to be surrounded by other regions with similar growth rates. However, it should be noted that this result may be ultimately caused by the fact that neighbouring regions tend in general to be relatively similar in many relevant economic aspects. To investigate this issue, we calculate again the Moran's I test of spatial autocorrelation for the regional growth rates conditional on the full set of control variables describe above. Although in this case the value of the statistic decreases somewhat, it continues to be positive and statistically significant. This indicates that the spatial autocorrelation observed in the regional growth rates is not driven exclusively by the geographical distribution of these variables. These results suggest that the model used to investigate the volatility-growth connection in Europe should take into account these spatial effects. In view of this, we now estimate by maximum likelihood the various spatial panel data models described in the previous section.[7]

INSERT TABLE 4 AROUND HERE

Column 2 of Table 3 presents the results from the spatial Durbin model, whereas the spatial lag model and the spatial error model are presented respectively in columns

[6]Similar results are obtained when the Moran's I test is calculated for the different regressors included in vector X. Further details are available upon request.

[7]According to Anselin (2010) there are two main approaches to estimate spatial econometric models: maximum likelihood (ML) and instrumental variables in the context of generalized method of moments (GMM). Nevertheless, Pace et al. (2010) show that the performance of the GMM approach is affected negatively when estimating a spatial Durbin model in the presence of spatially autocorrelated regressors. Accordingly, we use the ML approach in our estimations. Specifically, we employ the MATLAB routines written by Elhorst (2013), and the bias correction method proposed by Lee and Yu (2010).

3 and 4. Before continuing it is important to evaluate which is the best spatial specification in this context. To that end we calculate two likelihood-ratio test to find out if the spatial Durbin model can be simplified respectively to the spatial lag model ($H_0: \theta = 0$) or the spatial error model ($H_0: \theta + \rho\beta = 0$). As can be observed in Table 4, the null hypotheses of both tests are rejected. This implies that the spatial Durbin model is the appropriate specification in this context (Elhorst, 2010). In fact, this conclusion is consistent with the information provided by the various measures of goodness-of-fit included in Table 3.

As mentioned in the previous section, correct interpretation of the parameter estimates in the spatial Durbin model requires to take into account the direct, indirect and total effects associated with changes in the various regressors. Table 5 presents this information. Focusing on the main aim of the paper, our results show that the relationship between volatility and economic performance is positive and statistically significant, thus confirming the empirical evidence provided by our previous analyses and by Falk and Sinabell (2009). Nevertheless, this total effect is the sum of the direct and indirect impact of volatility on growth. If we consider the direct effect, Table 5 indicates that a change in the degree of volatility registered by a specific region does not exert a statistically significant impact on its growth rate. By contrast, the indirect effect shows that this change influence positive and significantly on the growth rates of the remaining regions. Accordingly, the economic performance of a particular region depends on the degree of volatility registered by the remaining regions, thus corroborating the relevance of spatial spillovers in this context.

INSERT TABLE 5 AROUND HERE

Table 5 also provides interesting information about the different control variables included in vector X. Thus, it should be noted that the direct effect estimates are in general statistically significant. In particular, the results obtained show that the regions with relatively low levels of GDP per capita tend to grow faster, confirming the existence of a process of conditional convergence across the European regions during the study period. Furthermore, the level of investment and the employment density of the various regions are positively correlated with the dependent variable, whereas the population growth rate is negatively associated with economic performance. The direct effects estimates also reveals that industry mix plays a relevant role in explaining regional growth. These findings are in general consistent with the empirical evidence provided by the literature on regional growth in Europe. In any case, it is important to observe that the direct effects displayed in Table 4 tend to be very similar to the spatial Durbin model coefficient estimates of the non-spatial lagged variables reported in Table 3. The differences between these measures are due to feedback effects that arise from spatial spillovers induced by each region in the whole system. Given that in our case these differences are not particularly relevant, we can conclude that feedback effects do not play an important role in this context. Table 5 also reveals that the indirect impacts are not statistically significant for any of the control variables included in our analysis, which implies that the effect of these variables tends to be confined to the region itself. As mentioned above, the sum of direct and indirect effects allows one to quantify the total effect on regional growth of the different control variables. When direct and indirect effects are jointly taken into account, Table 5 indicates that the total effect is statistically significant only in the case of initial GDP per capita, population growth and the share of employment in financial services.

The analysis carried out so far suggests the existence of a positive and statistically significant link between the intensity of output fluctuations and regional growth in Europe. In particular, our estimates seem to indicate that the observed relationship has to do mainly with the indirect effect of volatility on neighbouring regions. In the rest of this section we investigate the robustness of these findings.

As a first robustness test, we examine to what extent our results may be sensitive to the choice of the measure used to quantify the incidence of volatility in our case regions. To that end, we resort to an alternative measure of volatility used in the real business cycle literature that consists of the standard deviation of the GDP per capita gap (Hnatovska and Loayza, 2004). To calculate this measure, the trend of each region's GDP per capita series is estimated by applying the Hodrick-Prescott filter. The standard deviation of GDP per capita growth employed so far in the paper is based on the implicit assumption that the trend of GDP grows at a constant rate, whereas this measure allows the trend of GDP to follow a richer, time- and regional-dependant process. Table 6 shows the direct, indirect and total effects obtained when the two-way fixed effects spatial Durbin model is estimated again using the standard deviation of the GDP per capita gap to capture the relevance of the fluctuations of the business cycle in the sample regions. As can be seen, the total and indirect effects of volatility on regional growth continue to be positive and statistically significant. Accordingly our main findings still hold, thus confirming the robustness of our previous conclusions.

INSERT TABLE 6 AROUND HERE

Additionally, we examine the impact on the results of the spatial weights matrix used to capture the degree of spatial interdependence between the various regions. To do so we modify the spatial weights matrix employed so far by using different cut-off parameters above which spatial interactions are assumed negligible. In particular, the cut-off parameters selected coincide with the first, second and third quartile of the distance distribution (Le Gallo and Dall'erba, 2008). Table 7 shows the direct, indirect and total impact estimates for volatility obtained when these three alternative spatial weights matrices ($W(Q_1)$, $W(Q_2)$ and $W(Q_3)$) are employed to estimate different versions of the two-way fixed spatial Durbin model. The results show that our previous findings remain unchanged, regardless of the measure used to quantify the incidence of volatility in the sample regions. This reveals that the observed relationship between the variability of cyclical fluctuations and economic performance is robust to the specific spatial weights matrix used in the analysis.

INSERT TABLE 7 AROUND HERE

6 Conclusions

This paper has investigated the relationship between volatility and economic growth in a sample of 279 European regions over the period 1995-2008. To that end we have estimated a two-way fixed panel data model using spatial econometric techniques that allow one to take into account the relevance of spatial effects in the processes of regional growth in Europe. Although the reduced time span considered implies that any conclusion should be treated with some caution, our results show the existence of a positive and statistically significant relationship between volatility and economic growth in the European regions. This has to do mainly with the important role played in this context by spatial spillovers induced by volatility in neighbouring regions. The observed link is robust to the inclusion in the analysis of different explanatory variables that may affect regional growth such as the initial GDP per capita, the level of investment or industry mix. We have also checked that the results of the paper do not depend on the specific measure of volatility used, or the spatial weights matrix employed to capture the degree of spatial interdependence between the sample regions.

The results obtained in the paper have potentially interesting policy implications. At this point it needs to be recalled that the variability of cyclical macroeconomic fluctuations have typically been perceived as a negative phenomenon. This explains why reducing volatility has long been an important concern for policy-makers. Nevertheless, our results show that short-term instability is related to regional growth in the European context. In particular, the positive correlation detected between volatility and growth seems to suggest that traditional stabilization policies could ultimately be harmful for long-term growth in Europe. Although further research is required to confirm this conclusion, the possible trade-off between short-term stability and economic growth should not be overlooked by policy-makers.

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Figures and Tables

Figure 1: Volatility and regional growth, 1995-2008.

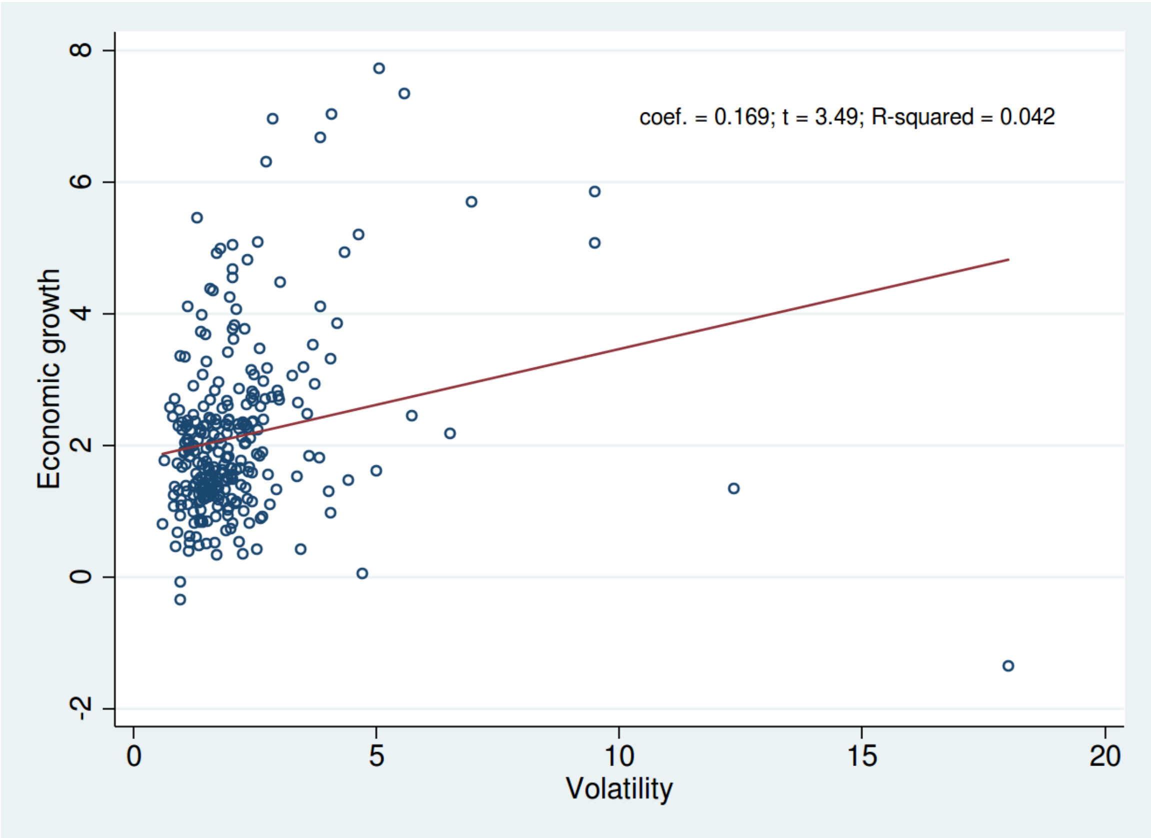

Table 1: The empirical relationship between volatility and regional growth.

Authors (year)	Sample	Period	Methodology	Results
Chatterjee and Shukayev (2006)	48 US states	1963-1999	Cross-section	Negative but not significant
Chandra (2003)	48 US states	1977-2001	Frontier estimation methods	Non-linear link. Positive for high-growth and negative for low-growth regions
Dawson and Stephanson (1997)	48 US states	1970-1988	Panel data	Negative and significant at the 10% level
Dejuan and Gurr (2004)	10 Canadian provinces	1961-2000	Cross-section and panel data	Positive and significant at the 10% level
Martin and Rogers (2000)	90 European regions (NUTS-1 and NUTS-2)	1979-1992	Cross-section	Negative and significant at the 5% level
Falk and Sinabell (2009)	1,084 European regions (NUTS-3)	1995-2004	Cross-section	Positive and significant at the 5% level
Ezcurra (2010)[a]	195 European regions (NUTS-2)	1980-2006	Cross-section	Positive and significant at the 5% level

Notes: [a] Sectorally disaggregated data only for manufacturing activities.

Table 2: Economic growth in various groups of regions.

	Two groups		Three groups		
	Low volatility	High volatility	Low volatility	Medium volatility	High volatility
Economic growth (%)	1.78	2.49	1.67	1.99	2.68
Regions	140	139	70	139	70
Equal means test (p-value)	21.42 (0.000)		17.74 (0.000)		

Notes: The classifications are based on the median (classification into two groups) and the first and third quartiles (classification into three groups) of the distribution of volatility.

Table 3: Estimation results: Volatility and regional growth.

Model	Non-spatial	Spatial Durbin	Spatial lag	Spatial error
Volatility	0.056*	0.041	0.051	0.047
	(1.82)	(1.08)	(1.36)	(1.26)
Initial GDP per capita	-0.099***	-0.090***	-0.095***	-0.098***
	(-8.95)	(-5.71)	(-6.93)	(-7.07)
Investment	0.027***	0.030**	0.027*	0.027*
	(2.29)	(2.04)	(1.86)	(1.89)
Employment density	0.506***	0.496***	0.482***	0.504***
	(4.30)	(3.20)	(3.34)	(3.46)
Population growth	-0.972***	-0.977***	-0.97***	-0.975***
	(-17.51)	(-14.28)	(-14.31)	(-14.35)
Agriculture	-0.025**	-0.023*	-0.025***	-0.025**
	(-2.51)	(-1.62)	(-2.08)	(-1.97)
Financial services	0.108***	0.087***	0.104***	0.104***
	(5.86)	(3.52)	(4.62)	(4.54)
Non-market services	-0.034***	-0.034**	-0.032**	-0.034***
	(-3.06)	(-1.99)	(-2.34)	(-2.40)
Neighbours' volatility		0.260**		
		(2.09)		
Neighbours' initial GDP pc		-0.010		
		(-0.22)		
Neighbours' investment		-0.036		
		(-0.97)		
Neighbours' empl. density		0.047		
		(0.10)		
Neighbours' pop. growth		0.399		
		(1.50)		
Neighbours' agriculture		-0.004		
		(-0.10)		
Neighbours' financial serv.		0.070		
		(1.01)		
Neighbours' non-market serv.		0.006		
		(0.14)		
Neighbours' econ. growth		0.164**	0.114	
		(2.05)	(1.55)	
Spatial autor. parameter (ξ)				0.190***
				(2.37)
Region-specific effects	Yes	Yes	Yes	Yes
Time-specific effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.399	0.417	0.403	0.404
Log likelihood	-1468.4	-1457.1	-1467.5	-1466.4
Observations	837	837	837	837

Notes: The dependent variable is in all cases the average growth rate of GDP per capita of the various regions measured over five-year periods. All the models include a constant (not shown). t-statistics in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 4: Spatial diagnostic tests.

	Statistic	p-value
Moran's I test: Unconditional	0.302	0.000
Moran's I test: Conditional	0.163	0.000
LR test: Sp. Durbin model vs. Sp. lag model	21.453	0.006
LR test: Sp. Durbin model vs. Sp. error model	19.317	0.013

Table 5: Spatial Durbin model: Direct, indirect and total effects.

Variable	Direct effects	Indirect effects	Total effects
Volatility	0.046	0.321**	0.373**
	(1.27)	(2.21)	(2.45)
Initial GDP per capita	-0.091***	-0.029	-0.118**
	(-5.83)	(-0.49)	(-2.24)
Investment	0.030**	-0.035	-0.005
	(1.99)	(-0.69)	(-0.105)
Employment density	0.499***	0.129	0.627
	(3.32)	(0.24)	(1.22)
Population growth	-0.972***	0.283	-0.689**
	(-14.60)	(0.93)	(-2.23)
Agriculture	-0.022	-0.01	-0.032
	(-1.56)	(-0.25)	(-0.84)
Financial services	0.089***	0.105	0.187**
	(3.56)	(1.30)	(2.53)
Non-market services	-0.033**	-0.002	-0.035
	(-1.98)	(0.13)	(-0.69)

Notes: t-statistics in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 6: Robustness analysis: An alternative measure of volatility.

Variable	Direct effects	Indirect effects	Total effects
Volatility	0.043	0.370**	0.413**
	(1.09)	(2.18)	(2.34)
Initial GDP per capita	-0.091***	-0.026	-0.117**
	(-5.83)	(-0.51)	(-2.34)
Investment	0.028*	-0.049	-0.021
	(1.84)	(-0.97)	(-0.42)
Employment density	-0.955***	0.327	-0.628**
	(-14.93)	(1.08)	(-2.04)
Population growth	0.477***	0.240	0.717
	(3.07)	(0.45)	(1.35)
Agriculture	-0.025*	0.005	-0.021
	-1.84	(0.11)	(-0.53)
Financial services	0.087***	0.090	0.177**
	(3.61)	(1.09)	(2.25)
Non-market services	-0.034**	0.022	-0.012
	(-2.07)	(0.45)	(-0.29)

Notes: Volatility is measured as the standard deviation of the GDP per capita gap. t-statistics in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 7: Robustness analysis: Alternative definitions of the spatial weights matrix.

Volatility	St. dev. GDP p.c. growth			St. dev. GDP p.c. gap		
Matrix	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
$W(Q_1)$	0.044	0.276**	0.320***	0.039	0.310**	0.350***
	(1.20)	(2.21)	(2.45)	(0.96)	(2.31)	(2.48)
$W(Q_2)$	0.045	0.309**	0.354**	0.041	0.347**	0.388**
	(1.20)	(2.23)	(2.45)	(1.00)	(2.27)	(2.51)
$W(Q_3)$	0.044	0.322**	0.365**	0.040	0.370**	0.414**
	(1.15)	(2.20)	(2.40)	(1.07)	(2.35)	(2.52)

Notes: t-statistics in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.