Regional differences in Okun's law and explanatory factors: Some insights from Europe

Abstract: Okun's law is one of the best-known stylised facts in the economic literature, as well as one of the most widely used policy tools. The aim of this paper, which utilises a comprehensive sample of 265 European regions by using annual observations covering the period from 2000 to 2019, is to deepen our knowledge of Okun's law from two perspectives. On one hand, by checking the existence and intensity of regional differences. On the other hand, by assessing the factors that explain them. To this end, in the first part, we apply a heterogeneous panel approach that deals with cross-sectional dependence, which allows us to obtain an average coefficient as well as region-specific coefficients. In the second part, a cross-sectional spatial model is used to uncover explanatory factors. Our findings reveal quite remarkable regional differences, as well as a somewhat geographical pattern in them. Moreover, they point out the importance of demographic factors (such as gender and age), labour market variables (share of employment in industry and construction, as well as self-employment and part-time employment and the severity of long-term unemployment), R&D expenditure, and some national institutional factors when it comes to explaining differences across regions.

Keywords: Okun's law; regional differences; heterogeneous panel approach; cross-sectional dependence; spatial dependence.

1. INTRODUCTION

The analysis of the validity of different economic laws has always been an important area of research in the economic literature. Among them, one of the most widely studied is the so-called Okun's law, which postulates an inverse relationship between changes in the real gross domestic product (GDP) and fluctuations in the unemployment rate. More precisely, Okun's seminal paper (1962) concludes that what has since been called the Okun's coefficient tends to be in the vicinity of 0.3, which means that, as long as the unemployment rate is above its natural rate, a 1% increase in GDP leads to a decrease in the unemployment rate of about 0.3 percentage points.

The significance and relevance of Okun's law rely, among other points, on its implications for economic policy. As it is evident, when policy-makers try to evaluate the effect of specific policies aimed at boosting economic activity, as well as, for instance nowadays in Covid times, the consequences of economic shocks, the value of the Okun's coefficient, provided that it is robust to such upheavals, becomes instrumental. Not only that, but even if Okun's law exhibits time-varying features, a study of its determinants would undoubtedly help to predict, at least to some extent, these changes over time. For these reasons, it is crucial to properly understand the relationship between economic growth and unemployment, as well as the factors that affect it.

Consequently, since the aforementioned seminal paper, there has been a vast literature attempting to assess the validity/intensity of Okun's law (see Perman, Gaetan, and Tavéra 2015, for a meta-analysis of this research). Initially, and somewhat in line with the standard specification of Okun's law restricted to aggregate macroeconomic variables, most papers addressed the study at the country level. However, as indicated, for instance, by Kangasharju, Tavéra, and Nijkamp (2012) and Palombi, Perman, and Tavéra (2015), there is an ongoing debate on the desirability of adopting a more general, multi-regional, perspective in which regions should be modelled as small self-sufficient (or autonomous) economies without overlapping, labour sharing or distortion of production flows.[1] Freeman (2000), in what can be considered the pioneering study of Okun's law at the regional level, argued that the use of regional data "has the potential to uncover geographic differences in the responsiveness of labour markets to changes in output" (Freeman 2000, 558). This regional approach also makes sense from a policy-determining standpoint if regions have competencies in economic policy or, at least, if there is a decentralization process that makes the role of regions increasingly important, the situation being different depending, above all, on the country concerned. In any event, even if regions do not have direct powers of intervention in the labour market, they have competencies over many policy domains (training, infrastructure and so on) that can be used to design policies that ultimately affect the labour market in one way or another.

Against this backdrop, many papers have recently studied Okun's law for various regional groupings within a country (covering the whole country or not). To name some of the most relevant in-depth studies at a regional level, we want to highlight Freeman (2000), Montero Kuscevic (2014), Pereira (2014), Basistha and Montero Kuscevic (2017), Gonzalez Prieto, Loungani, and Mishra (2018) and Guisinger et al. (2018) for the United States, Apergis and Rezitis (2003) and Christopoulos (2004) for Greece, Adanu (2005) for Canada, Villaverde and Maza (2009, 2021), Clar-López, López-Tamayo, and Ramos (2014), Melguizo (2017) and Bande and Martín-Román (2018) for Spain, Kangasharju, Tavéra, and Nijkamp (2012) for Finland, Binet and Facchini (2013) for France, Durech

[1] One way to ensure this would be to define regions based on the functional delimitations of the labour market (see e.g. Maza and Villaverde 2011). However, the advantages of redefining regions over the use of normative/administrative regions are, in many cases, not significant (Cörvers, Hensen, and Bongaerts 2009).

et al. (2014) for the Czech Republic and Slovakia, Palombi, Perman, and Tavéra (2015) for the United Kingdom, and Bod'a and Považanová (2020) for Italy.

While these papers, adopting a regional approach, achieve a consensus on the existence of a negative relationship between GDP growth and unemployment rates, the first point we would like to note is that the estimated coefficient is in many cases, although this result cannot be called a rule of law in the true sense, lower than the one found by Okun. Even more importantly for us here, we would like to stress that most previous work also finds significant differences between regions within the same country and, if we were to compare their results, between regions belonging to different countries.[2] Accordingly, we agree with Palombi, Perman, and Tavéra (2015, 6229) when writing that, "the reliability of Okun's coefficients is not only of paramount importance for macroeconomic policy [*as highlighted above*], but also for the regional distribution of unemployment rates in an open spatial system". In this sense, the idea of testing this law at the regional level is gaining importance, while the rationale of confining the analysis to a unique country is fading away. Hence, a more global study combining data from regions belonging to many different countries is missing.

Directly related to the foregoing, another salient point that is partially absent in the literature is an attempt to explain regional differences in the value of Okun's coefficient. Although there have been papers focusing their attention on particular factors, such as self-employment (Porras-Arena and Martín-Román 2019), labour market flexibility (Guisinger et al. 2018) or productivity (Villaverde and Maza 2009), to our knowledge only a nice paper published by Herwartz and Niebuhr (2011) dealt with this issue from a broader perspective.

[2] Although we have to admit they are not directly comparable since the results depend on the model specification and the applied methodology (Perman, Gaetan, and Tavéra 2015).

Bearing these considerations in mind, we contribute to the literature in several ways. The first lies in the case study as, by using Eurostat data, we consider a sample of 265 NUTS-2 administrative regions covering the EU (including the UK); the list of regions is included in Online Appendix 1. As for the sample period, it is important to point out that the methodology we employ, indicated in the next paragraphs, is quite data demanding. Therefore, we tried to keep the period as long as possible. It starts in 2000 because otherwise the number of blanks would have been prohibitively high, and ends in 2019 because at the time of starting the estimates included in this paper (May 2021) it was the last year available. In any case, to achieve this sample period we had to make some arrangements, which are explained in Online Appendix 2.

Another contribution of this study concerns the methodological approach. We absolutely agree with Boďa and Považanová (2020, 1118) in that "regional Okunian equations tend to be by default estimated separately with no regard to the fact that ... must be inevitably interrelated (correlated)" and, accordingly, propose a model in which all the regional equations are jointly estimated. Our model, however, does not meet the disaggregation condition brought out by Boďa and Považanová (2020), so the Okun coefficient we will obtain for the whole economy should be interpreted only as a mean coefficient — the average response of European regions to a change in output —, but not as a common Okun coefficient that fits all regions.[3] Nevertheless, as a counterpart, this paper may also methodologically contribute to the understanding of Okun's law at the regional level, as it addresses two of the essential, but frequently overlooked, features of spatial data by combining a heterogeneous panel approach with the treatment of cross-sectional

[3] Boďa and Považanová (2020) proposed, what can be perceived as a breakthrough in the related literature, a disaggregation framework in which the economy-wide Okunian equation is in agreement with the region-specific equations. They argue that if Okun's law is believed to hold at an economy-wise level, when descending to regions, traditional Okun equations are no longer applicable, but vary with region-specific compositions. Consequently, these authors developed an econometric framework where the economy-wide Okun's law implies that the regional equations add up to the economy-wide one.

dependence. According to previous comments, it is unquestionable that a homogeneous panel is not a valid option, as slope coefficients usually differ across territorial units (regions in our case). Therefore, a heterogeneous panel model is needed. However, it is not sufficient to obtain reliable results. Another issue, clearly related to heterogeneity, is often ignored: the presence of cross-sectional dependence. As pointed out by Chudik and Pesaran (2015, 3), "conventional panel estimators … can result in misleading inference and even inconsistent estimators, depending on the extent of cross-sectional dependence and on whether the source generating the cross-sectional dependence is correlated with regressors". In other words, if the assumption of independence across units is not met, standard estimators will be biased (see e.g. Bond and Eberhardt 2009; Sarafidis and Robertson 2009; Kapetanios, Pesaran, and Yamagata 2011). In view of that, we estimate Okun's law through a heterogeneous panel approach using estimators robust to the presence of cross-sectional dependence: the Common Correlated Effects Mean Group (CCEMG) estimator (Pesaran 2006) and the Augmented Mean Group (AMG) estimator (Bond and Eberhardt 2009; Eberhardt and Teal 2010).[4] These estimators allow obtaining, along with an average Okun's coefficient (for the interpretation of which it is necessary to bear in mind what is stated in the first lines of this paragraph), a region-specific coefficient. It is equally crucial to note that these estimators, in addition to coping with parameter heterogeneity and cross-sectional dependence, have some other strengths that make them particularly appropriate for our study: they yield robust estimates when dealing with problems that often plague empirical work, including endogeneity and omitted variable bias.

[4] There are alternative approaches dealing with cross-sectional dependence, such as the Fully Modified Ordinary Least Squares (FMOLS) and the Dynamic Ordinary Least Squares (DOLS) estimators proposed by Pedroni (2000, 2001). These estimators, which use cross-sectionally demeaned data, assume that cross-section dependence is driven by a single common source and that the response to the common factor is the same for all countries (Pedroni 2007), while the ones we employ capture more general forms of dependency.

Finally, we also try to enhance our comprehension of the relationship between variations in GDP and unemployment by explaining in depth the determinants of cross-regional differences. Having obtained region-specific coefficients, we propose a suitable cross-section model that tries to reveal the prime factors behind them. As we will see, a spatial model is designed, since standard tests for spatial dependence reveal that there are connections between the coefficients of neighbouring regions. This is indeed the first paper dealing with the explanation of Okun's coefficient differences by including geographical features, which, as we will figure out, are strongly significant. Apart from this factor, our general model will include variables relating to: 1) workers' cost and productivity; 2) educational level of workers; 3) demographic indicators; 4) employment and unemployment indicators; 5) R&D expenditure; 6) other indicators concerning labour market legislation at the national level. In doing so, we believe that, albeit with the inevitable limitations of data availability, a reasonably complete model is estimated. Data are drawn from the Eurostat database for the variables belonging to all but the last group, as data on collective bargaining and employment protection law are provided by other databases such as the International Labour Organization (ILOSTAT) and OECD Labour Statistics, respectively. Again, more information on the variables, as well as some adjustments that had to be made for the sake of consistency, is included in Online Appendix 2. In addition, descriptive statistics for the input data are shown in Online Appendix 3.

This article proceeds as follows. Section 2 presents the models and the empirical strategy. Section 3 contains the empirical results for the specification of Okun's law. Section 4 reports our findings on the main explanatory factors for regional differences in Okun's parameter. Section 5 concludes.

2. METHODOLOGICAL APPROACH: A TWO-STEP PROCEDURE

We follow a two-stage procedure to examine different features of Okun's law at the regional level in Europe. In the first step, by using a panel data approach, we estimate Okun's coefficients for each European region implementing, as said, estimators robust to the presence of cross-sectional dependence; in addition, the value of an average coefficient will be estimated to give a general idea about the extent to which Okun's law applies across European regional economies. It is important to recall that the heterogeneous panel approach dealing with cross-sectional dependence proposed here takes advantage of borrowing information across multiple regions, which makes it particularly attractive. In the second step, these regional coefficients are employed as the dependent variable of, due to data limitations, a cross-sectional model that attempts to explain regional differences. In this case, the inability to use panel data does not allow us to cope adequately with cross-sectional dependence as in the first step; for that reason, we lessen cross-sectional dependence by paying particular attention to one of the main reasons behind it: namely, spatial dependence.[5]

2.1 FIRST STEP: STANDARD OKUN'S APPROACH

Okun originally proposed alternative models to examine the relationship between output growth and variations in the unemployment rate. On one hand, his well-established law refers to the existence of an inverse relationship between the two, without paying attention

[5] Provided that there were no data limitations in terms of finding the determinants of regional differences in Okun coefficients, there is another methodological option that would overcome our two-step procedure. It would be, and indeed could be an avenue for future research, to formulate a hierarchical model with two panel data equations, namely Equation 1 (Okun equation with β as Okun coefficient) and Equation 2 (equation with β as response and its acclaimed predictors), so that Equation 2 is posited and estimated simultaneously with Equation 1 under a set of statistical assumptions by using a suitable algorithm.

to the direction of causality. In this regard, we pick causality running from output to unemployment, which is the most common specification; in doing so, we are interpreting Okun's law as a labour demand function. That is to say, in our model the unemployment rate is taken as the explained variable while output is considered as the regressor.

On the other hand, there are basically two standard versions of Okun's law: the so-called gap and first-differences models. In our view, the latter retains a substantial advantage over the former: it allows the researcher to work with observable data. Accordingly, we resort to the first-differences method "which does not require any predefinition of trend nor additional hypotheses for the extraction of the statistical relationship" (Fontanari, Palumbo, and Salvatori 2020, 251). At any rate, this decision is usually not crucial since the results, as in the case of the seminal paper written by Okun, tend to be relatively similar (Ball et al. 2019).

Finally, there have been several papers extending some of Okun's original specifications from distinct perspectives, either by dynamising the model or by including other variables that can also affect the evolution of the dependent one (here unemployment, as mentioned above). Nevertheless, we are not going to extend the model for several reasons. Firstly, because our methodology reduces to a minimum the omitted variables problem. Secondly, because the second part of this paper tries precisely to explain regional differences in the sensitivity of unemployment to changes in output.

With all these considerations in mind, we adopt as a benchmark a basic model that reads as follows:

$$\Delta u_{it} = \alpha_i + \beta \Delta y_{it} + \mu_{it} \quad (1)$$

where Δu_{it} denotes the percentage point change in the unemployment rate in region i at time t, α_i corresponds to the region-specific intercept, Δy_{it} is the percentage growth rate of real output, and μ_{it} is the corresponding error term.

Starting from what could be called, at least in terms of its widespread use, the standard version of Okun's law, which usually meets the requirements in terms of stationarity due to the definition of both variables (they are indeed stationary as we will see below), we are going to introduce some changes in line with the aim of the paper. These changes are also related to our methodological approach. As indicated, we want to estimate a different coefficient for each region, so β becomes β_i and a heterogeneous panel model is considered:

$$\Delta u_{it} = \alpha_i + \beta_i \Delta y_{it} + \mu_{it} \qquad (2)$$

Furthermore, in contrast to the stationarity issues, we believe that the model does not satisfy the assumption of independence across units. The root of this belief is that a glance at the data (not displayed for space reasons) shows that changes in both unemployment and output are not randomly distributed. Indeed, since regions within an economy tend to have highly correlated unemployment and output patterns, these changes follow a sort of geographical pattern (see Online Appendix 4). Thus, when it comes to merging data in a panel model some dependence across regions (cross-sectional dependence) is expected (and confirmed as reported in the subsequent section), which renders standard estimation techniques useless. To conclude, one must employ econometric techniques that address cross-sectional dependence. More precisely, for the sake of robustness, two different approaches are pursued: CCEMG and AMG estimators.

The CCEMG estimator proposed by Pesaran (2006), when applied to our case, intends to include additional variables in Equation (2). As Pedroni explains, "the basic idea behind this approach is to use estimates of the cross-sectional averages from each of the variables to proxy for multiple common factors, and to include these in the regression with member-specific coefficients in order to allow for heterogeneous responses" (Pedroni 2007, 443-444). Therefore, the cross-sectional averages of the dependent and independent variables (in our case, $\overline{\Delta u_{\iota t}}$ and $\overline{\Delta y_{\iota t}}$) must be added in Equation (2). This approach also assumes that the error term follows a multi-factor structure defined by $\varepsilon_{it} = \vartheta_i f_t + \pi_{it}$, where f_t is the vector of common unobserved shocks affecting all regions although with different intensities (ϑ_i), which are allowed to be stationary or nonstationary, serially correlated and possibly correlated with $\overline{\Delta y_{\iota t}}$ (see, for technical issues, Holly, Pesaran, and Yamagata 2010; Kapetanios, Pesaran, and Yamagata 2011). This is an important point, as our sample period is rather long and characterised by different phases of the business cycle as well as strong economic shocks. However, the second part of the error term, the individual-specific errors (π_{it}), is assumed to be distributed independently of both the unobserved common factors and the regressors, but allowed to be weakly dependent across countries and serially correlated over time.

As a result, in order to evaluate Okun's law, we estimate the following equation:

$$\Delta u_{it} = \alpha_i + \beta_i \Delta y_{it} + b_{i0}\overline{\Delta u_{\iota t}} + b_{i1}\overline{\Delta y_{\iota t}} + \varepsilon_{it} \quad (3)$$

where all the variables have the previous meanings and, as proposed by Pesaran, the average Okun's law coefficient, which only gives a general overview and should not be interpreted, as noted, as a common coefficient that suits all regions, can be computed as the simple mean of the regional coefficients ($\hat{\beta}_{CCEMG} = N^{-1}\sum_{i=1}^{N}\hat{\beta}_{i,CCEMG}$), being N=265.

The AMG estimator, by Bond and Eberhardt (2009) and Eberhardt and Teal (2010), is also used. Its main idea is to account for cross-sectional dependence by including a 'common dynamic process' that is extracted from the year dummy coefficients of a pooled first-difference regression. This process represents, as indicated by Bond and Eberhardt (2009, 2-3), "the levels-equivalent mean evolvement of unobserved common factors across all countries" (regions here). Consequently, we first estimate a standard first-difference version of the Okunian Equation (2), with *T-1* year dummies whose aim is to capture the common factor and from which we collect the year dummy coefficients ($\hat{\sigma}_t^*$). Next, these coefficients are added to Equation (2), along with a linear trend term (t) to capture the omitted idiosyncratic processes that evolve in a linear fashion over time. Therefore, the new model is as follows:

$$\Delta u_{it} = \alpha_i + \beta_i \Delta y_{it} + d_i \hat{\sigma}_t^* + c_i t + \epsilon_{it} \qquad (4)$$

where d_i (c_i) captures the potential heterogeneous effects of the common factor (linear trend), and the average coefficient can be, once again and following the Pesaran and Smith (1995) mean group (MG) approach, calculated as the simple average of the individual region estimates ($\hat{\beta}_{AMG} = N^{-1} \sum_{i=1}^{N} \hat{\beta}_{i,AMG}$).

2.2 SECOND STEP: AN ATTEMPT TO EXPLAIN REGIONAL DIFFERENCES

The second step consists of estimating a cross-section explanatory model of the regional Okun's coefficients obtained in the first step. Given the similar results yielded by the two alternative estimators (as we will in Section 3), we will perform the analysis for the CCEMG case, so the estimated coefficients at regional level ($\hat{\beta}_{i,CCEMG}$) become the dependent variable of the explanatory model. As explanatory variables, we will include some of the potential factors that, based on previous works in this branch of the literature exploring the link between unemployment rates and GDP from both a theoretical and empirical perspective, as well as data availability, could help to explain regional differences. Moreover, due to the presence of spatial dependence in the estimated coefficients (see again below), a spatial lag model is employed to incorporate potential spatial effects explicitly. As a result, the explanatory model reads:

$$\hat{\beta}_{i,CCEMG} = \delta + \rho \sum_j w_{ij} \hat{\beta}_{j,CCEMG} + \boldsymbol{\varphi X_i} + \tau_i \quad (5)$$

where $\sum_j w_{ij} \hat{\beta}_{j,CCEMG}$ denotes the spatial lag of the dependent variable, ρ is the spatial lag parameter capturing the primary spillover effects across neighbouring regions, and $\boldsymbol{X_i}$ is a group of explanatory variables with associated parameters $\boldsymbol{\varphi}$. As for the definition of the spatial lag, w_{ij} denotes the elements of the distance/spatial-weight matrix W between each pair of regions i and j. To be precise, spatial weights are defined as the (standardised) inverse of the square of the distance between the corresponding centroids. We use a square matrix to impose a heavy penalty on distance. In any case, our results do not depend significantly on the distance matrix, as we also tried with other versions — such as the contiguity matrix, the inverse of the distance, or matrices considering different cut-offs — and the results were quite similar to those reported in the next section.

As for the vector of explanatory variables, we include a battery of factors that can potentially affect the nexus between output and unemployment. Specifically, the following groups of factors are considered, whose variables will be thoroughly explained when commenting on the results:

- **1. Indicators of workers' cost and productivity**. We consider variables such as wages (compensation of employees per hour) and productivity (GDP divided by working hours). We also explored a combination of both by calculating unit labour costs, but the results were roughly the same, as we will discuss.
- **2. Educational attainment**. We add, on the one hand, the share of workers with primary education in employment (accurately, less than primary, primary and

lower secondary), and, on the other hand with tertiary education. We also tried replacing any of the above with secondary education, but once again the results were not sensitive to this choice.

- **3. Demographic indicators**. We consider the proportion of young people (aged 15 to 24) and women in total employment, as well as the growth of the labour force. In this case, we tried an alternative definition of 'youth' by modifying the age cohort (we tried 15-35), the results being somewhat different as we will see. The rate of growth of the active population is also included.
- **4. Some labour market indicators**. The percentage of self-employed and the percentage of part-time workers are included. The share of long-term unemployed (12 months or more) of the total unemployed is equally considered. Regarding the industry-mix, the percentages of employment in construction and industry are chosen, as well as that of the public sector. At this point, some branches of the service sector were also tested but were not significant in any case.
- **5. Innovative capacity of a region**. We add, as another potential determinant of the responsiveness of unemployment to production, R&D expenditure (defined in euros per inhabitant), since it is a good proxy for innovative capacity. Although this variable can also be defined as R&D expenditures as a percentage of GDP, the results are very similar to those shown here and, therefore, robust.
- **6. Other indicators relating to labour market legislation at the national level**. In this case, the coverage of collective bargaining (in %), and an indicator of employment protection law (strictness of employment protection – individual and collective dismissals (regular contracts)) are taken into account. For this group, data must be collected at the national level.

Finally, it is important to note that, to include these variables, we have to decide the date at which they are measured since, unlike the first step, here we are forced to employ a cross-sectional regression. Our initial idea was to use the mean of the sample period, but the issue is that, especially in some cases such as productivity, wages, industry-mix, self-employment, and long-term unemployment, potential problems of endogeneity became apparent. More precisely, the values of these variables are related to the sensitivity of unemployment to output, i.e., to the dependent variable of the proposed model. Therefore, to narrow endogeneity, which is always troublesome, the most satisfactory solution is to consider these variables at the beginning of the sample period or, in the case of regions where this is not possible because data coverage starts after the year 2000, at the closest one.[6]

3. ESTIMATING OKUN'S LAW

As indicated in the previous section, Equation (1) could be considered a standard version of Okun's law (although not realistic for the reasons already stated), while the Okunian Equation (2) is not only more convincing but also more appealing for us, since we are interested in getting a different coefficient for each unit of analysis. Equations (3) and (4) were proposed assuming the presence of cross-sectional dependence in the model. Therefore, this is the first econometric issue we have to handle.

[6] If the sensitivity of unemployment to output significantly affects features such as industry mix and/or some type of contract, for example, regressions that do not somehow account for this simultaneity are more likely to provide unreliable results.

In fact, rather than taking problems of cross-sectional dependence for granted, we should check for its presence in the error term of Equation (2).[7] More specifically, we compute Pesaran's (2004) CD statistic, Frees' (1995) FRE statistic and Friedman's (1937) R_{AVE} statistic, which are appropriate, as in our case, for heterogeneous panels $T<N$. As can be seen in Table 1, all the three tests strongly reject the null hypothesis of no cross-sectional dependence. Therefore, empirical evidence confirms the suitability of Equations (3) and (4) for testing Okun's law.

Another fundamental issue to be addressed before proceeding with the estimation of these equations is to determine whether the variables included exhibit unit root properties. When the presence of cross-sectional dependence is confirmed, we conduct the cross-sectionally augmented IPS test (CIPS), proposed by Pesaran (2007), which is based on cross-sectionally augmented Dickey-Fuller regressions (CADF). Table 2 reports the results obtained using 1-3 lags when a constant and a constant and a trend are included in the model. As can be observed, it suggests that both variables are stationary, since the non-stationarity hypothesis is rejected in both cases whatever the test specification.

Therefore, we can rely on the results obtained from the CCEMG and AMG approaches, which are reported, in terms of the average coefficient, in Table 3. Thus, the results seem to support the validity of Okun's law at the regional level in Europe, since, on average across all regions, there is a negative and significant relationship between output performance and unemployment rates. These results, which are consistent with most empirical studies to date, differ however in the strength of the relationship. As an example, the average Okun's coefficient obtained is lower (about half) than that exposed

[7] In any case, as shown in Online Appendix 4, one of the potential causes of cross-sectional dependence, namely spatial dependence, is present in the variables included in the model, which can be considered a clear sign of the breakdown of standard econometric assumptions.

in the seminal paper.[8] For the CCEMG estimator, it attains a value of -0.186, which becomes slightly lower in absolute terms (-0.149) for the AMG estimator.

Concerning the individual coefficients, to save space we merely show the coefficients obtained by the CCEMG approach, since the correlation between them and those for the AMG estimator is 0.86. Furthermore, instead of presenting the results obtained for each region in an extensive table (265 coefficients), we have chosen to display them on a map (Figure 1). In any case, for detailed Okun coefficients and fixed effects for each region, see Online Appendix 5.

Having said that, as for regional Okun's coefficients we want to give some other descriptive statistics that provide additional information. Thus, skewness takes a value of -1.99 and kurtosis is equal to 14.07. Moreover, a simple glance at the aforementioned Figure 1 reveals that, although 85% of the Okun coefficients are negative, there are important differences between regions. Being the mean, as noted, -0.186, the minimum value is reached in Calabria (-1.92) and the maximum in Ceuta (0.55). Another essential trait you can get from the map is that the coefficients are not randomly distributed, but are clustered geographically. From this point of view, it seems that Southern European regions are characterised by higher coefficients (in absolute value) than, above all, some Central, Eastern and Northern European regions. Put differently, spatial dependence is likely to be one of the main features of the regional distribution of Okun's coefficients. Due to the importance of this result in modelling the search for potential drivers, as we are doing next, we computed the most commonly used test of spatial dependence, namely the Moran's I statistic (Moran 1948). It reaches a value, when using the inverse of the square distance as weight matrix (although the results are very robust to changes in it), of

[8] In any case, these comparisons are, as highlighted in footnote 1, vague for the sake of profound methodological differences.

0.089 (p-value = 0.000), so we can state that the existence of positive spatial dependence is found to exist and, therefore, it should be effectively considered in the explanatory model whose findings are shown below.

Ultimately, and just for the sake of robustness, we would like to point out that the results, both average and individual, are quite stable against sample and model variation. On one hand, to assess the stability of Okun's law, we computed for the CCEMG estimator all 15-year rolling regressions possible (although, as indicated, the econometric technique requires as long a data series as possible), and the results show that the average coefficient was quite stable, always between -0.15 and -0.20.[9] In addition, to minimise data loss we also tried by only removing the years 2008 and 2012, which could be considered a kind of 'outliers' due to the negative growth rates recorded in the EU. In this case, the average coefficient reached a value of -0.183, roughly the same as with the whole sample. Not only that but also the correlation coefficient between the regional results was 0.96. On the other hand, we refined the specification of the Okun's law model by including some dynamics; to be precise, for the potential presence of serial correlation, we added the time lag of both unemployment and GDP changes and, again, the CCEMG estimator was calculated. On this occasion, the mean coefficient was -0.187 and the correlation at the regional level 0.75. Finally, and partly thanks to the reading of Boďa and Považanová (2020) work, instead of computing the average coefficient as a simple mean (Pesaran 2006) we calculated it as a weighted average, where the weighting corresponded to the percentage of workforce in each region.[10] The average coefficient was, in this case, slightly higher (-0.195). In a nutshell, it seems clear that our findings are indeed robust,

[9] More specifically, the coefficients for the different windows were -0.198 (2000-2014), -0.200, -0.182, -0.184. -0.171, and -0.154 (2005-2019).
[10] Needless to say, it is far from the approach of Boďa and Považanová (2020), but we believe it is an appropriate additional robustness test.

so in the second part of the paper we are going to focus our attention only on the original CCEMG results presented in Table 3 and Figure 1, as well as in Online Appendix 5.

4. EXPLAINING REGIONAL DIFFERENCES

As noted in the methodological section, it is now time to analyse the determinants of the regional differentials in Okun's law coefficients; namely, the explanatory model specified above. The first point we want to make has to do with the interpretation of the results. As the dependent variable is negative, to avoid confusion we are going to pay attention to the magnitude of Okun's coefficients. In other words, a positive estimated coefficient associated with any variable, which implies a direct link between it and the dependent one, has to be interpreted in this case as a decrease in the magnitude (absolute value) of the Okun's coefficient, i.e. a decrease in the sensitivity of unemployment to output. Having clarified this simple yet important point, we estimate Equation (5) including the potential explanatory factors mentioned in Section 2. The first column of Table 4 shows the results obtained.

Starting with the coefficient related to the spatial lag of the dependent variable, it is positive and statistically significant. In other words, previous signs of the existence of spatial dependence — the coefficient of a region is similar to those of neighbouring regions — are confirmed even after including a long battery of variables trying to explain Okun's coefficients at a regional level. There are certainly local spatial spillovers, whose nature could range from agglomeration (Marshall-Arrow-Romer externalities based on intra-industry agglomeration or Jacobian externalities via inter-industry agglomeration) to competition (Porter externalities based on intra-industry local competition). Our results thus prove these spillover effects tend to cluster regions regarding their unemployment rate's sensitivity to output changes (an accurate view of the factors explaining spatial dependence in unemployment can be found in Cuéllar-Martin, Martín-Román, and Moral 2019).

Continuing with the first group of variables (groups are indicated by shaded/non-shaded areas), we wanted to test, on one hand, whether the sensitivity of the unemployment rate to output growth depends on workers' costs. Several papers indirectly address this issue. For instance, the seminal papers by Feldstein (1976) and Baily (1977) detected a positive relationship between wages and layoffs, which could affect the size of the coefficients in hard times. In a similar line, Blanchard et al. (1992) postulate that high wages lead to unemployment. However, our findings indicate that there is no evidence of the existence of any relationship between them, which indeed is not so strange since empirical regularity does not support the theoretical postulates (Blanchflower and Oswald 1995). On the other hand, if one thought from the point of view of workers' productivity, a potential hypothesis, in line with the labour hoarding argument (Horning 1994), would be that the higher the level of productivity, the less likely the existence of mass layoffs. Once more, however, the coefficient is not different from zero.[11] Lastly, as indicated in explaining the factor groups, merging these two variables so that a single one denoting unit labour cost is included does not modify the results. Consequently, the first group of potential factors plainly fails.

[11] It should be noted that, despite the problems of simultaneity, we also considered including the growth rates of both wages and productivity in the equation. Both variables turned out to be significant, as expected, with a negative coefficient for the former and a positive coefficient for the latter. In any case, since the econometric problems in the model specification were evident, we decided not to keep these variables. This decision was helped by the fact that their inclusion did not affect the results of the other groups to which we will now turn our attention.

The second group refers to educational attainment. Our idea, also under the labour hoarding argument, is that the higher the level of human capital the higher the chance of being hired or the lower the possibility of being fired (see, for instance, the influential work by Bell 1964, 1973, who coined terms such as ‘post-industrial society’ and ‘knowledge economy’). However, neither the coefficient of primary education nor that of tertiary education turns out to be different from zero, so there is no indication of human capital as a significant factor in explaining regional differences in the unemployment response to changes in output. When secondary education is included instead of either of the above, neither is significant again.

The third group regards demographic indicators. In this group, we included the growth of the active population to capture a greater availability of workers in the production function. It was already considered by Okun and related papers such as Guisinger et al. (2018). However, the result, once again, indicates no effect, as, although positive in line with expectations, the coefficient is not statistically significant. On the contrary, our findings reveal that the higher the share of women and youth (15-24 years old) in total employment, the lower the magnitude of the Okun’s coefficient, that is, the connection between GDP growth and unemployment. As for the female labour force, it is in line with the results obtained by previous work, which concludes that men are more sensitive to changes in the business cycle (e.g. Hutengs and Stadtmann 2014; Bod’a and Považanová 2021). Regarding youth, the findings reported here are not in agreement with those reported in previous articles in which a similar variable was not significant (Herwartz and Niebuhr 2011; Guisinger et al. 2018).[12] This paper conveys that a high percentage of

[12] We would also like to point out that several papers conclude that young people are more sensitive to changes in the business cycle (Zanin 2014, 2018; Dunsch 2016). Although our findings seem to be at odds with that, we want to recall that the approach is completely different, as these papers directly estimate the Okunian equation for different age cohorts; thus, a straight comparison is not valid. In any case, the message of this paper is that the crucial point for this overreaction of young people is their low participation in the labour market, since they are then massively hired in good times, while in times of crisis their dismissals

youth employment reduces the sensitivity of unemployment to output. Several tentative explanations can be touched upon. On the one hand, during economic upswings, if the percentage of youth is already sizeable it is hard to reduce unemployment through the recruitment of young people. In times of crisis, on the other hand, our finding seems to be consistent with the idea that young employees are more resilient than older generations as their ability to adapt to change is greater, as well as with the fact that employers might follow a policy of replacing one batch of young workers with another batch (very high turnover on a last-in-first-out basis).[13] Finally, it is important to note that, by modifying the definition of youth (considering workers between 15 and 34), the coefficient, although still positive and significant, is reduced by almost half, so that the effect is indeed especially strong when considering people in their first years of working life.

Concerning the largest group, which deals with several labour market indicators, the results are more satisfactory than the previous ones. Indeed, almost all the variables included are statistically significant at least at 10%. Starting with the industry mix, the coefficient associated with the industrial sector is positive and different from zero, suggesting that regions with more intense industrial activity show comparatively on average low Okun coefficients; therefore, industry is a sector that does not seem to be quite sensitive, in relative terms, to changes in production. As for construction, the opposite is true. Its sign is, as expected, negative, evoking that the construction sector responds strongly to output changes (Morris and Heathcote 2005). Another variable included in this pool comprises the share of employment in the public sector, although it is the only case in this group with a non-significant coefficient. In any event, its positive

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do not cause (as their weight was already small in itself) a notable increase in total unemployment. Consistent with this, when instead of the share of young people in employment we consider their share in the labour force, the coefficient is not statistically different from zero.

[13] Another possible explanation could lie in the fact that young workers are more likely to seek new and better jobs even during hard times (Ryan 2001).

sign conveys the idea, if any, that the public sector could be, in terms of output-unemployment fluctuations, more stable than the private one, so the linkage between output and unemployment tends to be smaller in regions with a larger share of people engaged in public services.

Another variable of the labour indicator's group reaching a positive coefficient, although statistically different from zero in this case, is the share of self-employment. This result somewhat coincides with that obtained by Porras-Arena and Martín-Román (2019), who in a paper focused on this issue conclude that, within the theoretical framework assuming the decision of becoming self-employed as a cost-benefit decision, push factors (related to insufficient opportunities) dominate pull factors (new business opportunities are perceived). In other words, they convey the idea that self-employment is a kind of "refuge employment" (necessity entrepreneurship), showing in many cases a countercyclical behaviour. As for the part-time employment variable, it appears that those regions with a higher proportion of part-time workers report a slightly stronger unemployment response to output, in line with the idea that this type of contract is more sensitive to the phase of the economic cycle due to its lower earnings as well as lower firing and hiring costs (Lester 1999). As indicated by Bentolila and Saint-Paul (1992), the introduction of low firing costs contracts increases the cyclical response of employment.[14] Finally, the regions in which long-term unemployment represents, as a rule, a greater proportion of total unemployment coincide with those in which the Okun's coefficient is higher in absolute value. This result can be interpreted as a signal that the poor functioning of the labour market, one of the most apparent symptoms of which is long-term unemployment (e.g.

[14] The same probably happens with temporary jobs. Data on temporary jobs in NUTS2 regions are not available, but it is likely that they would not have been included in the equation in any case due to multicollinearity issues.

Adda and Triggari 2016), causes a more vigorous response of unemployment to output fluctuations.[15]

The fifth group actually comprises a single variable, namely the R&D expenditure. In principle, we could postulate that those regions where it is more prominent will be, in theory, more resilient. However, empirical evidence has shown that the patterns that dominate R&D spending in many cases include pro-cyclical dynamics, whereby they increase in boom times and consequently create new jobs, but decrease in recessions and thus contribute to job destruction/non-creation. This work points to the second reasoning, as its coefficient is negative and significant, i.e., R&D provokes a stronger response of unemployment to variations in production.[16]

The sixth group is composed of national variables (identical value for all regions belonging to the same country) trying to proxy, among other things, some features of labour market legislation. Thus, according to theory, employment protection tends to reduce the magnitude of the Okun's coefficient, as it makes the labour market less volatile; parameter estimates of models reported in several studies suggest that job dismissal regulations reduce both hiring and firing and thus worker flows (e.g. Bentolila and Bertola 1990; Mortensen and Pissarides 1994). Our result is in line with theory as well as with the empirical work of Herwartz and Niebuhr (2011). As for the level of collective bargaining, the coefficient is not different from zero, which to a certain extent seems to agree with Gartner, Schank, and Schnabel (2012), who show that collective

[15] For all the variables included in this group, due to their peculiarities and despite possible endogeneity problems, we also tested with the mean value of the sample period instead of the initial one; the results were roughly the same.

[16] For R&D expenditure, we took the mean value for the sample period rather than the initial one. Although one of the practical reasons supporting this decision is that the date for which data are available is quite different depending on the region at hand (Online Appendix 2), the main one is that the mean value better captures this cyclical/counter-cyclical performance and potential endogeneity problems are not, in this case, as important as in the previous group.

bargaining does not cause downward wage rigidity in times of rising unemployment.[17] An additional point to be mentioned, quite significant but not shown for reasons of space, is that when including these two 'national' factors in the model, the value of the coefficient linked to the spatial lag of the dependent variable decreases markedly (from 0.570 to 0.494). The conclusion we can infer is that, apart from others, these factors are decisive to understanding the similarities in coefficient values between neighbouring regions.

Finally, we re-estimated our explanatory model but excluded data on regions belonging to some key countries. Our aim was, while maintaining enough data to ensure the reliability of the results, to assess their robustness and, moreover, the role fulfilled by these regions in relation to some of the explanatory factors. More precisely, we excluded (1) Spanish and Italian regions, as representatives of the 'Southern regions'; (2), French and German regions, representing the EU's two largest economies, with leading positions in European politics; (3) United Kingdom regions, as the country no longer belongs to the EU. The results are disclosed in the remaining columns of Table 4.

Prominent differences when excluding the Spanish and Italian regions refer to youth, industry-mix, self-employment and part-time employment, as well as employment protection. Based on the results, it seems that these regions were behind the positive coefficient linked to youth since, especially the Italian ones, were characterised by a reduced initial level of young employees and high Okun's coefficients (in magnitude). From this result, our own, quite tentative, conclusion is that Southern regions may have managed to reduce unemployment in boom times by hiring young people.[18] Concerning

[17] In any case, the effect of collective bargaining depends on the degree of centralization (Calmfors and Driffill 1988). Not only that, Soskice (1990) questioned Calmfors and Driffill's approach to centralisation of collective bargaining because it excluded coordination mechanisms.

[18] As pointed out by a referee, patterns may be more intricate. In some countries, for instance, there have been recent attempts in labour policy to reduce employment of otherwise retired people who make

the industry mix, standing out the Spanish case now, it seems that Southern regions were the main cause of the role played by industry and construction; this is quite remarkable in the second case since the share of this sector in Spain has always been excessively high, making these regions quite vulnerable to the business cycle (Angulo, Mur, and Trívez 2018; Pontarollo and Serpieri 2021). It also appears that the importance of self-employment is rather limited to these types of regions, where entrepreneurship out of necessity is comparatively common. Findings also suggest that the volatility of part-time employment is more notable in these Southern regions, where part-time workers maintain substantially less attachment to the labour market than full-time workers. Finally, it seems that the role of employment protection as a factor reducing labour market instability is exceptionally strong in Southern countries.

When German and French regions are removed, the rate of growth of the active population becomes positive and significant. This was the hypothesis underlying the inclusion of this variable, i.e., that the increase in the labour force in good times would reduce the coefficient because regions would be unable to absorb this increase and, at the same time, reduce unemployment. Since it is only true for this subsample, it appears that these regions were indeed able to absorb the population growth, and their inclusion led to the non-significance of the variable with the entire sample. Besides, the coefficient associated with the spatial lag of the dependent variable becomes non-significant, so the bond between neighbouring regions is deeper in the two main countries of the EU. The effects of industry-mix and part-time employment, although consistent with the case of Southern regions, are much less important.

employment earnings alongside their old-age pension. At this stage, it must be admitted that, without more detailed information, any explanation is tentative, providing a hypothesis for further work.

Finally, the exclusion of UK regions mainly affects the role of tertiary education, which now is significant. The UK possesses a large tertiary-educated population and yet does not have significantly lower (in magnitude as always) Okun's coefficients. As Coulter (2016, 210) points out, "analysis of the past two decades also indicates that the United Kingdom has replaced a larger share of the medium-skilled jobs that have been lost with lower (as opposed to higher) skilled jobs than other European countries". Although less significant, it is interesting to note the increased role of 'national' factors when excluding the UK, which is likely related to the well-known idiosyncrasies of this country, whose institutions do provide workers with relatively weak protection (Heyes and Lewis 2014). As for part-time, our findings indicate that the UK, a country where this sort of contract is comparatively common, is not behind the expected higher sensitivity of unemployment to output. In fact, they indicate that when the UK regions are not considered, this relationship emerges more clearly. One potential explanation is the narrowing of the earnings gap between part-time and full-time workers that has occurred in the UK (e.g., Nightingale 2021).

5. CONCLUSIONS

This paper has assessed the strength of Okun's law for the European regions between 2000 and 2019. Using a heterogeneous panel data approach dealing with cross-sectional dependence, the paper obtains not only an average coefficient for Europe as a whole, but also region-specific ones, so that regional differences are captured. In the second part of the paper, a spatial model is employed to determine factors that explain these differences.

Our findings confirm the validity of Okun's law for this broad case study (average coefficient), but more importantly, at the same time reveal substantial differences between regions. While it can be said that on average a one-percentage-point increase/decrease in the output growth rate decreases/increases the unemployment rate by nearly 0.2 percentage points, there are regions in the vicinity of a one-to-one relationship. A key factor in these differences is that regions with a high/low Okun's coefficient tend to be clustered, and this feature holds (especially in French and German regions) even once potential explanatory factors for regional disparities are taken into account. Other explanatory factors in shaping differences across regions are the share of women and youth in employment (mainly in the Southern regions), as they make Okun's coefficient smaller in magnitude. Apart from these, indicators such as the share of self-employment and part-time employment allow us to understand what happened in certain areas, mainly in the Southern regions where: on one hand, self-employment is primarily used in downturns as a way of escaping unemployment, and; on the other hand, part-time employment increases volatility in the labour market, which contributes to the greater reactivity of unemployment to production. Long-term unemployment, which can be taken as a sign of a malfunctioning labour market, also leads to a greater sensitivity of unemployment to output. In addition, the industry mix arises as another factor explaining differences, since there are sectors such as construction that are particularly affected by the business cycle. The role played by R&D expenditure is also noteworthy, because it increases Okun's coefficients due to the fact that these expenditures are concentrated in boom times. Finally, some institutional factors, especially the level of employment protection, help to explain differences across regions.

The results of this paper should be considered when using Okun's law relationship from a policy-oriented perspective. From the point of view of the EU as a potential optimum currency area, the notable differences across regions suggest that a common monetary policy would cause rather heterogeneous effects (see, e.g., Perman and Tavera 2007; Herwartz and Niebuhr 2011; Guisinger et al. 2018). Put differently, if policymakers were to use European data to inform their decisions, i.e., aggregate data as a basis for policy implementation, these would most likely have a highly differentiated effect across regions, which could easily increase social and political tension.

Hence, specific regional policies (or at least policies with different intensity depending on the region) must be applied to tackle unemployment issues. Besides, it seems to be proven that the evolution of the unemployment rate in any region is heavily dependent not only on its output change but also on the growth experiences of neighbouring regions, so that regionally coordinated supply and demand policies could be key to improving the situation of the labour market.

Finally, it is important to recall that Okun's law is an essential forecasting tool. Indeed, it is commonly used when computing potential output, which plays an essential role in settling the expansionary or contractionary stance of policies (Fontanari, Palumbo, and Salvatori 2020); a classic example, indicated above, is the link between the output gap and the monetary policy of the European Central Bank. In the same vein, as indicated by Monastiriotis and Martelli (2021), Okun's law is routinely used to assess the expected effects of a shock.[19] According to our results, forecasters should bear in mind, when specifying models, the situation of each economy with respect to the explanatory factors outlined above. In other words, attention should be devoted, as hitherto, to the Okun's coefficient as a measure of adjustability, but more attention should be placed on the labour market of the regions, since changes in them may condition the relationship between

[19] It is also useful to check the reliability of publicly available forecasts, as presented by An et al. (2019) with respect to IMF unemployment forecast.

output and unemployment. As an example, our findings pointed out that when pro-youth employment policies are implemented, a decrease in the coefficient should be expected since the higher the embeddedness of young people in the labour market, the lower the reactivity of unemployment to output. If this further information is not included in the potential model, its predictive power could be very low, thus yielding erroneous decisions from a political point of view.

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Table 1. Tests for cross-sectional dependence

Tests	*Statistics*	*p-value*
CD (Pesaran)	112.911***	0.00
R_{AVE} *(Friedman)*	7.391***	0.00
FRE (Frees)	699.243***	0.00

Notes: *** indicates rejection of the null hypothesis of no cross-sectional dependence at the 1% level. For $T \leq 30$, Frees' test provides critical values from the Q distribution.
Source: Own elaboration.

Table 2. CIPS panel unit root test

	CADF(1)	*CADF*(2)	*CADF*(3)
		No Trend	
Δu_{it}	-3.797***	-3.815***	-3.843***
Δy_{it}	-3.609***	-3.676***	-3.689***
		With Trend	
Δu_{it}	-3.799***	-3.839***	-3.852***
Δy_{it}	-3.790***	-3.837***	-3.883***

Notes: *** indicates rejection of the null hypothesis of non-stationarity at the 1% level.
Source: Own elaboration.

Table 3. Estimated CCEMG and AMG results

	CCEMG	AMG
Δy_{it}	-0.1859*** (0. 0137)	-0.1489*** (0. 0115)

Notes: Dependent variable Δu_{it}. Standard errors are reported in parentheses. *** indicates significance at 1%.
Source: Own elaboration.

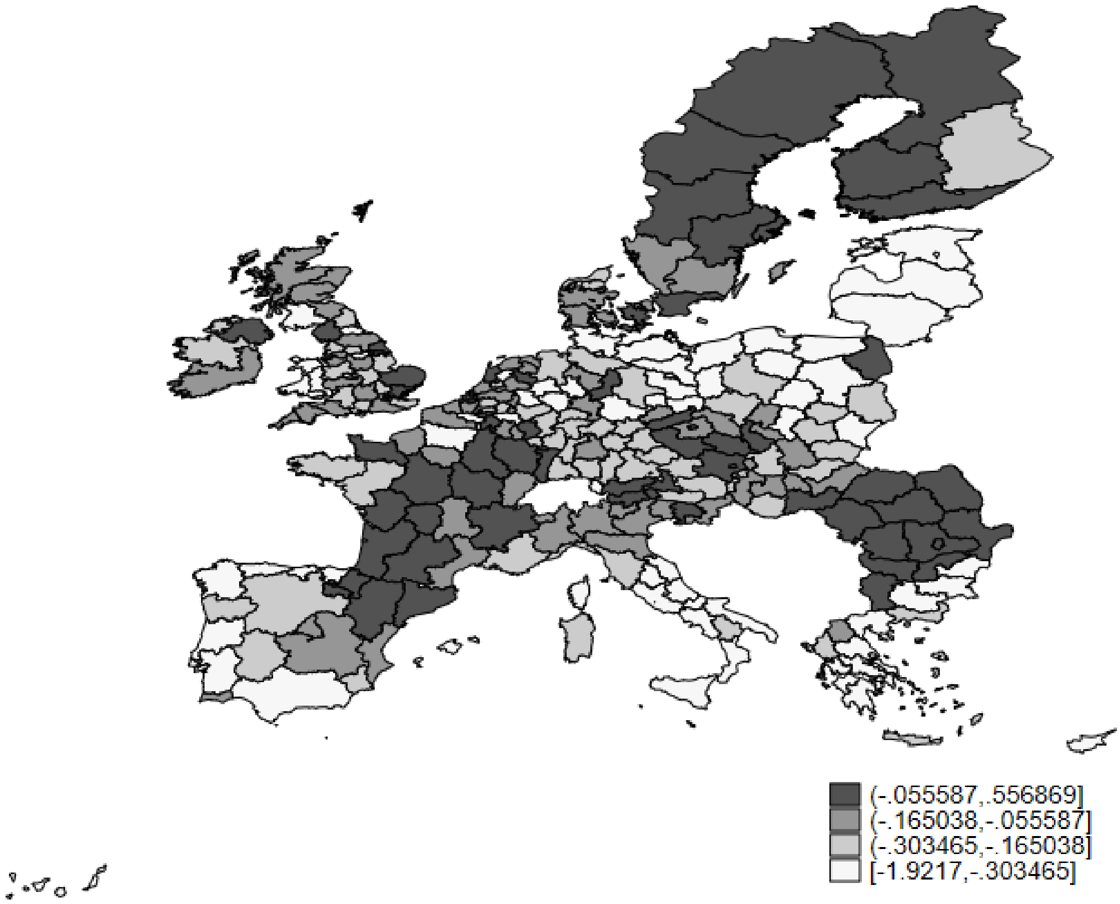

Figure 1. Okun's coefficient by region

Table 4. Explanation of regional differences in Okun's law coefficient

	Whole sample	Without Spanish/Italian regions	Without French/German regions	Without UK regions
$Constant$	-0.830**	-0.629	-1.158**	-0.957**
	(0.027)	(0.120)	(0.01)	(0.018)
$Spatial\ lag$	0.494**	0.448***	0.111	0.256
	(0.020)	(0.005)	(0.529)	(0.148)
$Wage$	0.004	-0.001	0.015	0.009
	(0.627)	(0.899)	(0.251)	(0.418)
$Productivity$	0.000	0.003	-0.005	-0.002
	(0.999)	(0.592)	(0.430)	(0.730)
$Primary\ education$	0.000	-0.001	-0.001	-0.001
	(0.903)	(0.664)	(0.267)	(0.384)
$Tertiary\ education$	0.003	0.001	0.003	0.005**
	(0.207)	(0.638)	(0.267)	(0.037)
$Women$	0.012**	0.010*	0.014***	0.012**
	(0.010)	(0.058)	(0.008)	(0.013)
$Youth$	0.015**	0.007	0.019**	0.020***
	(0.034)	(0.281)	(0.025)	(0.008)
$Active\ Population\ Growth$	0.026	0.006	0.055*	0.040
	(0.248)	(0.766)	(0.074)	(0.105)
$Industry$	0.005**	0.002	0.006**	0.006**
	(0.043)	(0.351)	(0.049)	(0.042)
$Construction$	-0.013*	-0.005	-0.010	-0.024***
	(0.078)	(0.499)	(0.284)	(0.007)
$Public\ sector$	0.005	0.000	0.004	0.003
	(0.167)	(0.944)	(0.264)	(0.476)
$Self-employment$	0.006*	0.004	0.009**	0.008**
	(0.064)	(0.154)	(0.028)	(0.019)
$Part-time\ employment$	-0.004*	-0.002	-0.004	-0.007***
	(0.070)	(0.462)	(0.158)	(0.009)
$Long$	-0.004***	-0.003***	-0.004**	-0.004***
$-\ term\ unemployment$	(0.001)	(0.005)	(0.019)	(0.006)
$R\&D$	-0.038**	-0.026*	-0.039*	-0.062***
	(0.023)	(0.100)	(0.062)	(0.002)
$Employment\ protection\ law$	0.051*	0.033	0.059	0.096***
	(0.085)	(0.218)	(0.103)	(0.009)
$Collective\ bargaining$	0.001	0.001**	0.001*	0.003***
	(0.121)	(0.042)	(0.077)	(0.003)
Log likelihood	56.7	83.02	31.11	56.7

Notes: Dependent variable $\widehat{\beta}_{i,CCEMG}$. p-values are reported in parentheses. $^{***(**)(*)}$ indicates significance at 1%(5%)(10%).
Source: Own elaboration.