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Labor supply and the business cycle: The "Bandwagon Worker Effect"

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Abstract

The relationship between labor force participation and the business cycle is a common topic in economic literature. However, few studies have examined if the cyclical sensitivity of labor force participation is influenced by social effects. In this paper, we construct a theoretical model defining a relatively new hypothesis, the Bandwagon Worker Effect (BWE). We use spatial econometrics techniques to test the existence of the BWE in the local labor markets in Spain. Our results reveal a positive spatial dependence in the cyclical sensitivity of labor force participation that decreases as we fix a laxer neighborhood criterion, which verifies the existence of the BWE.

Keywords: Labor force participation, business cycle, regional labor markets, bandwagon effect, spatial dependence.

JEL Codes: C23, D03, E32, J21, R23.

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1. Introduction

The aim of this paper is to analyze how the relationship between the business cycle and labor force participation (LFP) may be influenced by social effects[1]. The so-called Bandwagon Effect (BE) is now a useful element to better understand the demand for goods and services (Leibenstein, 1950). Because the labor supply is, ultimately, demand for leisure, we deem that the BE might also operate in the labor market. Notably, some studies have already explored this possibility (Blomquist, 1993; Vendrik, 1998; Grodner and Kniesner, 2006; 2008). Additionally, papers have investigated the influence of social influence over individuals' decisions to participate in the labor market (e.g., Clark and Summers, 1982; Kapteyn and Woiitiez, 1987; Romme, 1990; Vendrik, 1998; Neumark and Postlewaite, 1998). Or more closely related to this research, because they have explicitly adopted a spatial approach, we refer to Fogli and Veldkamp (2011) and Halleck-Vega and Elhorst (2017)[2].

However, no one has studied the effect of that social influence on the cyclical sensitivity of the aggregate labor supply. Our research links this social effect to the cyclical properties of LFP and coins a relatively new hypothesis, the Bandwagon Worker Effect (BWE). The relationship between the business cycle and LFP has produced much academic work. This body of research has produced two key concepts: Added Worker Effect (AWE) and Discouraged Worker Effect (DWE). Here, we develop a theoretical

[1] By social effects in this paper we mean the social influence over an individual's behavior of the perceived average behavior of his/her peers. Manski (1993, 2000) and Dietz's (2002) name them social interactions or neighborhood effects and account for the different types of social effects (i.e. endogenous effects or peer effects, correlated effects and exogenous effects). Martín-Román et al. (2015) delves into that issue from a spatial analysis perspective.

[2] There are a number of papers analyzing some spatial aspects of the aggregate labor markets, published recently (e.g., Overman and Puga, 2002; Cracolici et al., 2007; Halleck-Vega and Elhorst, 2014; 2016), that are somehow related to this research too.

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framework in which the BWE interacts with the AWE and DWE to better understand cyclical movements in the labor supply. In a second step, we test empirically whether the BWE is a significant factor when considered together with the AWE and the DWE. According to our review of the literature, we are the first to present and discuss this hypothesis[3]. This is the value added of the paper.

The critical assumption of this research is that an individual's labor supply decisions are conditioned to a certain extent by his/her neighbors' decisions regarding their labor market activity. To formalize that idea, in our conceptual framework, individuals emulate to some degree their neighbors' behavior with regard to their labor supply decisions. The aforementioned social effect may also be interpreted by an aggregation process, as a positive spatial correlation among the spatial units considered. Thus, the previous discussion implies that the participation rate (PR) of a spatial unit surrounded by high-level PR spatial units would higher than otherwise and vice versa. This positive spatial correlation between the levels of labor PRs can be translated into a positive spatial correlation between the cyclical sensitivity of those PRs. Hence, we assume that a geographical neighborhood is a tool to capture the degree and the intensity of the social effects, as will be explained in greater detail later[4]. We assume global spatial correlation for four reasons. First, from a conceptual point of view, we posit that the social phenomenon analyzed should cause feedback effects because of its nature. Second, the literature on this topic indicates the same direction (Fogli and Veldkamp, 2011). Third,

[3] Fogli and Veldkamp (2011) do build a theoretical model to account for social effects on female LFP from a geographical perspective and test that hypothesis by using spatial econometrics techniques, as we do in this research. Nevertheless, neither the theoretical setting nor the empirical strategy is the same as ours. Moreover, the aim of their investigation differs from ours.
[4] See, for instance, Martín-Román et al. (2015).

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our theoretical setting also assumes a global spatial dependence. Finally, econometric reasons, discussed later, support this view.

We use Spanish data because the amplitude of the Spanish business cycle is larger than that of most of the developed countries. Furthermore, it is possible to find a sufficiently long time series and with an appropriate spatial disaggregation to conduct feasible a study such as this[5]. In addition, Spain is made up of 50 provinces (NUTS-3 regions)[6], which allows us to apply spatial econometric techniques with a high degree of reliability and accuracy.

The results obtained show a positive, significant global spatial dependence in the cyclical sensitivity of the LFP in the Spanish provinces. According to our theoretical approach, this finding proves that the BWE is a key phenomenon to help understand the overall functioning of the aggregate labor market. Moreover, we find that as the neighborhood definition becomes laxer, the strength of the social effect diminishes. This outcome is consistent with the theoretical framework developed here.

The remainder of the work is organized as follows. Section 2 offers a review of the literature related to the topic. Section 3 develops the theoretical model. Section 4 presents the methodology used to study the relationship between the labor PRs and the business cycle and to test the BWE. Section 5 describes and explains the results obtained in the cyclical sensitivity analysis and in the spatial dependence analysis. Section 6

[5] In this vein, Ball et al. (2017), Bande and Martín-Román (2018), and Porras-Arena and Martín-Román (2019) have provided empirical evidence of the large size of the Spanish business cycle, particularly with regard to the labor market outcomes.
[6] The 50 Spanish provinces correspond to the third level (NUTS-3) of the Nomenclature of Territorial Units for statistics, see: http://ec.europa.eu/eurostat/web/nuts/overview.

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includes extensions to the empirical analysis and sensitivity checks. Section 7 offers economic policy implications. Finally, Section 8 sums up the most relevant conclusions.

2. Literature review

Based on the discussion in Section 1, several strands of literature are relevant to our inquiry. First, the research on the LFP pattern over the business cycle constitutes the conceptual basis on which we build our approach. Spatial analysis is also at the core of this research because our theoretical framework predicts a spatial relationship that affects the LFP reaction to the business cycle and because such a relationship is then tested by means of spatial econometrics' techniques. Thus, the literature that has analyzed spatial labor markets' functioning is also of interest. The last strand of literature has examined the influence of social effects on labor market outcomes, and we pay particular attention to research that has used spatial analysis to determine the influence of such social effects.

The relationship between the LFP and the business cycle has been an active research topic for decades. The interest is probably because of its crucial implications on the correct measurement of actual unemployment and, as a consequence, on the correct intensity of the monetary and fiscal policies to be implemented. The two key concepts in the relationship between the business cycle and the LFP are the AWE (Woytinsky, 1940; Humphrey, 1940) and the DWE (Long, 1953; Mincer, 1962) hypotheses.

According to the conventional view of the AWE (Woytinsky, 1940), some breadwinners lose their jobs during an economic downturn. As a consequence, their

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spouses would experience a reduction in non-labor income, reducing their reservation wage, and at an aggregate level, increasing the labor force. The opposite would be true in an economic boom. Hence, this effect establishes an overestimation of the unemployment rate during downturns and recessions and vice versa during strong economic growth periods.

The original idea of the DWE (Long 1953, 1958) holds that when the likelihood of finding a job decreases, some workers cease their active job searches (i.e., they become inactive), and that the opposite occurs when the likelihood of finding a job increases. The rationale behind this is that as the expectations of finding a job decrease, the transaction costs linked to the search process could exceed the benefits expected. In summary, through this effect, the LFP exhibits a pro-cyclical pattern of an underestimation of the unemployment rate in booming periods and an overestimation during downturns and recessions.

As these two hypotheses predict opposite patterns for LFP changes throughout the business cycle, determining which prevails over the other is an empirical question. The observed evidence on these two effects is mixed: Some studies have demonstrated a prevalence of AWE over DWE, and others have demonstrated that DWE is stronger than AWE, depending on various factors of the labor market analyzed (e.g., geographical location, gender). For instance, Wachter (1972, 1974) and Tano, (1993) have demonstrated that both effects offset each other.

Specifically, in Maloney (1987) and Emerson (2011), the AWE has dominated in the United States. Del Boca et al. (2000) and Ghignoni and Verashchagina (2016) have

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identified the same effect for Italy. Parker and Skoufias (2004) detect empirical evidence of a prevailing AWE in Mexico, and Gałecka-Burdziak and Pater (2016) do the same for Poland. In the Spanish case, this effect is dominant in Prieto-Rodríguez and Rodríguez-Gutiérrez (2000, 2003), and partially in Congregado et al. (2011).

Regarding the research to find a prevailing DWE, the pioneering work by Long (1958) and Clark and Summers (1981), Leppel and Clain (1995), or Benati (2001) have demonstrated that this effect predominates in the United States. In Darby et al. (2001), the DWE is predominant for the case of women between 45 and 54 years old in Japan, France, and the United States. Similarly, empirical evidence of a noticeable DWE, in net terms, has been provided by Lenten (2001) and O´Brien (2011) for Australia, Österlhom (2010) for Sweden, and Martín-Román and Moral de Blas (2002) and partially Congregado et al. (2014) for Spain.

We easily imagine from the aforementioned discussion that spatial analysis of the regional labor markets will be a key element in this research. Some seminal works in this area have been provided by Marston (1985), Blanchard and Katz (1992), Decressin and Fatas (1995), or Taylor and Bradley (1997). More specifically, the role played by space in the analysis of different topics concerning the labor market at the macro level has attracted much attention. For instance, studies have analyzed the differences in the unemployment rates among territories (e.g., countries, regions) and their persistence in time (Molho, 1985; Jimeno and Bentolila, 1998; Overman and Puga, 2002; López-Bazo et al. 2002, 2005; Filiztekin, 2009; Kondo, 2015; Halleck-Vega and Elhorst, 2016; Cuéllar-Martín et al. 2018). Furthermore, other studies have focused on the role that space plays in the process of matching individuals in the labor market (Haller and Heuermann, 2016).

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In any case, this paper intends to advance the analysis of the cyclical properties of the LFP. We consider that social effects, proven to influence several economic outcomes, play a critical role in explaining cyclical variations in the LFP. The influence of social group behavior on an individual's decisions has been labeled in the literature as social effects, or in some cases, Peer Effects (Manski, 1993, 2000; Dietz, 2002).

In the case of economics (i.e., microeconomics), a type of social effect has been named BE for the demand for goods and services. This effect establishes that the behavior of an individual is determined by his/her personal features and influenced by the actions and decisions of his/her peers (Leibenstein, 1950; Pollak, 1976; Granovetter and Soong, 1986; Van Herpen et al., 2009). Because the labor supply is a demand for leisure, we deem that the BE might operate in labor markets too.

Thus, we are interested in studies that have applied the social effects approach to analyze participants' behavior in the labor market. For example, Hellerstein et al. (2011) and Hellerstein et al. (2015) have highlighted the role of networks defined by residential neighborhoods in employment and re-employment opportunities, especially for minorities and less-skilled laborers. These studies have demonstrated empirical evidence to support the idea that social effects, or network effects in their terminology, are essential to understand local labor market functioning. Loog (2013) also shows that social effects are critical to understanding certain outcomes observed in the labor market. More precisely, this author analyzes the significance of social effects in relation to working hours by using a sample of public workers in Germany between 1993 and 2005. Similarly, Collewet et al. (2017) point out that there is a small peer effect in the working

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time of a sample of Dutch male employees from 1994 to 2011. Similar results are in Weinberg et al. (2004)[7].

Even more closely related to the ultimate aim of the paper, we could emphasize that the connection between social effects and the labor supply from a microeconomic perspective has produced literature too. For instance, Blomquist (1993) elaborates a model where the worker's preferences regarding labor market outcomes are interdependent with other individuals' behavior. Vendrik (1998, 2003) establishes that workers' labor supply is determined not only by his/her individual preferences but also by other individuals' labor market participation decisions. A similar approach can be found in Kapteyn and Woittiez (1987), Neumark and Postlewaite (1998), Romme (1990) or Grodner and Kniesner (2006, 2008). Finally, Woittiez and Kapteyn (1998) and Maurin and Moschion (2009), who have also demonstrated relevant social effects in the labor supply of women.

Notwithstanding, our study combines the micro and macro perspectives, and then adds a spatial dimension. Thus, there exists a critical body of research closely related to this investigation that has analyzed spatial dependence among LFPR. Table 1 summarizes this strand of literature. We elaborated on this by referencing Halleck-Vega and Elhorst (2017) and other studies.

First, a group of studies has offered, from a more general standpoint, empirical evidence on the importance of accounting for spatial effects in the labor market analysis

[7] Other works that have adopted a different perspective regarding social influences on individuals in the labor market are Casella and Hanaki (2008), Tassier and Menczer (2008), and Koursaros (2017).

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(Elhorst, 2001; Cochrane and Poot, 2008; Halleck-Vega and Elhorst, 2014, 2017). A second group of studies has more specifically focused on the LFPR analysis from a spatial perspective. Elhorst and Zeilstra (2007) investigate the underlying factors behind the heterogeneity of LFPRs within the European regions. Similarly, Elhorst (2008) concludes that LFPRs appear to be strongly correlated in time, weakly correlated in space, and parallel their national counterparts. Möller and Aldashev (2006) explicitly link the social effects conceptual framework to spatial analysis, which we do in this paper. In particular, those authors employ spatial econometric techniques to test the existence of social effects in the LFPRs in West and East Germany.

Finally, studies have focused on female labor market participation. Falk and Leoni (2010) provide empirical evidence on a negative spatial relationship among female LFPRs in Austrian districts. In a similar context, Liu and Noback (2011) apply a spatial error model (SEM) to detect the determinants of female LFPR in the Netherlands. From a more theoretical point of view, Fogli and Veldkamp (2011) propose a conceptual framework to explain the entry of women in the labor force over the last decades in the EEUU counties. Finally, Kawabata and Abe (2018) explore the presence of spatial patterns in the LFPR of women in the metropolitan area of Tokyo.

3. Theoretical model

To introduce the idea of BWE, we construct a labor market participation model. We are interested in the extensive margin of the labor supply; thus, we consider a fixed working week. In this manner, labor supply choices coincide with participation decisions. Some examples of this type of model are found in Boeri and van Ours (2013), Cahuc et al.

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(2014), and Martín-Román (2014). However, our model is extended to consider the effects of unemployment[8]. Following the distinction made by Rodrik (2015) between critical and non-critical assumptions, the structure of the model comprises of one critical assumption (i.e., the mechanism driving our results), which we call the Core Theoretical Mechanism, and a set of other non-critical assumptions (discussed in appendix 1).

Core Theoretical Mechanism. *Labor supply decisions depend on individual determinants and on an individual's neighbors' decisions. The spatial neighborhood affects individual choices related to the labor supply*[9]*. The PR of one specific area depends on the PRs in neighboring areas, and all remaining areas are also mutually affected. This mechanism leads to a global spatial dependence (i.e., feedback effects are operating that are associated with the BWE).*

The goal of this theoretical framework is twofold: defining and formalizing a second-order theoretical effect, namely, the BWE, and, second, connecting such an effect with a well-established procedure in spatial analysis: Global Moran's I. This would be an extension of the well-known BE established for the demand for goods and services (Leibenstein, 1950). In the present context, a direct means of introducing the notion of BE into the labor supply decisions is just by letting the reservation wage be a function of the PR of neighboring areas, $PR^N(Z)$, which also depends on the business cycle[10]. In formal terms,

[8] In appendix 1, we develop the theoretical structure underlying the concept of BWE, explain the concept of reservation wage, describe the aggregation process, define the variables used, and formally derive the notions of the AWE and DWE.
[9] This behavioral supposition has been proposed, more or less explicitly, by Fogli and Veldkamp (2011), Halleck-Vega and Elhorst (2014) or Halleck-Vega and Elhorst (2017).
[10] The variable PR^N should be thought of as a sort of a weighted average of the different PRs in the neighboring areas. In a later section, we provide further details to explain how we measure this in practical terms.

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$$PR = \phi(w, w_M^R[y(Z), p(Z), PR^N(Z)]) \tag{1}$$

According to the basic idea of BE, an individual would demand more of a good or a service if his/her social environment does so. Thus, in our context, a worker demands relatively more leisure, all the things equal, if he/she lives in a society of leisure lovers, and vice versa. Therefore, if the PR in the neighboring areas increases, the reservation wage of the median worker should decline: $\partial w_M^R / \partial PR^N < 0$. Taking this last effect into account, we might formally state the total effect of the business cycle on labor market participation by expression (2), instead of by (A12) in the appendix:

$$\frac{\partial PR}{\partial Z} = \underbrace{\frac{\partial PR}{\partial w_M^R}}_{(-)} \left(\underbrace{\frac{\partial w_M^R}{\partial y} \cdot \frac{\partial y}{\partial Z}}_{AWE(+)} + \underbrace{\frac{\partial w_M^R}{\partial p} \cdot \frac{\partial p}{\partial Z}}_{DWE(-)} + \underbrace{\frac{\partial w_M^R}{\partial PR^N} \cdot \frac{\partial PR^N}{\partial Z}}_{BWE(?)} \right) = \beta^+ \gtreqless 0 \tag{2}$$

In expression (2), the BWE affects the cyclical behavior of PRs in an a priori unknown form because despite the sign of $\partial w_M^R / \partial PR^N < 0$ being well-defined, $\partial PR^N / \partial Z$ could be either positive or negative, depending on whether the AWE or the DWE prevail in the neighboring areas. Thus, we cannot affirm that β^* (the PR cyclical sensitivity without the BWE, defined in appendix 1) is either higher or lower than β^+. Notably, the BWE is relevant to understanding labor market participation because the second-order derivative calculated in expression (3) has a well-defined positive sign:

$$\frac{\partial^2 PR}{\partial Z \partial \left(\frac{\partial PR^N}{\partial Z} \right)} = \frac{\partial PR}{\partial w_M^R} \cdot \frac{\partial w_M^R}{\partial PR^N} > 0 \tag{3}$$

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Expression (3) indicates that the PR cyclical pattern of a specific area is positively related to the cyclical pattern in the PRs of neighboring areas. That is, if we measure the cyclical sensitivity of the PR in a specific region i (by means of an econometric procedure) and call it β_i^+, it ought to be positively related to the average PR cyclical sensitivity in the neighboring areas (of region i), which is denoted here by β_i^N. Formally, this could be represented by means of expression (4) and

$$\frac{\partial \beta_i^N}{\partial \beta_i^+} > 0 \quad (4)$$

The mathematical relationship shown in (4) could be graphically depicted as line *AA'* in Figure 1. However, this apparently trivial diagram has a powerful, straightforward interpretation: It would correspond to Moran's scatterplot (with the axis being properly centered around the normalized values of β_i^+ and β_i^N), a widely used tool in spatial analysis[11]. Put differently, Figure 1 bridges the gap between the conceptual framework and the empirical strategy in this study. Thus, our theoretical setting allows us to test easily and directly the BWE, and this testing is relevant to understanding the PR cyclical patterns. This part of the study is performed in a subsequent section.

4. Methodology

To test for the presence of the BWE, the first step is to estimate the cyclical sensitivity of the labor force. Thus, we employ a panel dataset composed of the 50 Spanish provinces

[11] We acknowledge that Moran's I test is currently too basic in spatial econometrics. However, in this research, Moran's I only plays the role of linking the theoretical setting with the empirical strategy. Nevertheless, to check the sensitivity and robustness of the results, much more sophisticated spatial econometrics tests are conducted in the empirical sections of the paper.

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for the period 1977–2015. As explained, we attempt to verify if the AWE, the DWE, or none of those effects prevail in these territories. To achieve our objective, we initially rely on equation (5):

$$CPR_{it} = \alpha + \beta_i \cdot CUR_{it} + D_{2001} + \mu_i + \varepsilon_{it} \quad (5)$$

where CPR_{it} refers to the cyclical component of the PR of province i in year t; α is the constant of the regression; CUR_{it} is the cyclical component of the unemployment rate; D_{2001} is a dichotomous variable, which takes the value 1 after the year 2001, and 0 otherwise;[12] μ_i represents the provincial fixed effects; and ε_{it} denotes the disturbance term. In this case, α and μ_i are fixed constants, and we need additional restrictions to estimate them. One method to do that is to introduce the restriction $\sum_{i=1}^{K} \mu_i = 0$. Then, the fixed effect μ_i represents deviations from the mean intercept α[13]. Using this procedure, we obtain 50 estimations of the cyclical sensitivity of the LFP (β_i), one for each Spanish province.

The main problem is obtaining the CPR_{it} and the CUR_{it} because the cyclical component of the variables cannot be observed and must be estimated. The economic literature uses several methods for obtaining these cyclical components, and one is the Hodrick–Prescott filter (Hodrick and Prescott, 1997) (HP). The first step to apply this filter is to choose a value for the λ parameter. In this case, we use λ=400 because this

[12] This dichotomous variable is introduced because, in 2001 a methodological change was implemented that affected how unemployment was measured. This methodological change may be seen at http://www.ine.es/epa02/meto2002.htm.
[13] Hsiao (2014).

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value is very common in the economic literature when working with annual data (Backus and Kehoe, 1992; King and Rebelo, 1993; Maravall and Del Río, 2001).

We also refer to studies that have questioned the use of the HP filter. An influential paper in this vein is Hamilton (2018), which points out three limitations related to the application of this technique: 1) appropriateness when applied to different types of economic series, 2) problems in obtaining future predictions, and 3) difficulties in choosing coherent values of the λ parameter according to the data structure (e.g., monthly, quarterly, yearly). Under these circumstances, the HP filter can yield spurious dynamic relationships and erroneous estimations of the cyclical components. To solve the first limitation, the Quadratic Trend procedure (QT) is used as an alternative to obtain the cyclical component[14]. Regarding the second limitation, we do not make predictions but focus on the analysis of the cyclical sensitivity. Finally, and with regard to the choice of λ, the cyclical component is obtained again with the HP filter and λ= 100[15]. In addition, and as a measure of robustness, an estimate is also made with quarterly data and λ= 1600. Notably, some estimates that have applied the Hamilton filter have been conducted to obtain the cyclical component of the time series, and the outcomes are similar to those of our baseline models[16].

We estimate equation (5). If β_i is statistically significant and greater than 0, the AWE prevails in that zone. If β_i is less than 0 and statistically significant, the DWE dominates. Finally, if the value of β_i is not significant, neither of the previous effects

[14] This method is based on a linear regression of the data that we want to decompose, using the linear and the quadratic component of a trend as independent variables. In this manner, we extract both the trend component of the data previously mentioned and the disturbance term, which is identified by the cyclical component

[15] Econometric alternatives to these two methods are available, such as the Baxter-King filter (Baxter and King, 1999) and other more complex strategies (e.g., Phillips curve, Kalman filter).

[16] Results are available upon request from the authors.

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dominates the other. To avoid various econometric problems (e.g., spurious correlation) we must test if the cyclical components of the PR and the unemployment rate are stationary. Thus, we conduct several unit-root panel data tests (table A1 in Appendix 3)[17]. Based on the results, we conclude that our cyclical components, obtained with the HP (for both λ parameter values) and the QT procedure, are stationary.

We have estimated the 50 cyclical coefficients of the PR at a provincial level. In the next step, we apply spatial analysis to test for the presence of the BWE. First, we must define a neighborhood criterion by means of a weight spatial matrix. Further, to check the robustness of the results, we conduct the analysis by employing various alternative spatial weight matrices[18]. To detect global spatial dependence, we compute Global Moran´s I, (Moran, 1948), defined as follows[19]:

$$I = \frac{n}{S_0} * \frac{\sum_{i,j}^{n} SW_{i,j}\ (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \qquad (6)$$

where n is the sample size, SW_{ij} refers to the components of the spatial weights' matrix, x_i represents the value of variable x in province i, x_j represents the value of variable x in province j, S_0 is equal to $\sum_i \sum_j SW_{ij}$, and $\bar{x}$ corresponds to the sample mean of variable x. Global Moran's I takes values between 1 and -1. If the values are close to 1, there is positive spatial dependence, and there is negative spatial dependence if the values are

[17] These panel tests are basically an extension of the ADF test (Augmented Dickey–Fuller) applied to a panel data structure. In the case of the Harris–Tzavalis test, Levin–Lin–Chu test, and Breitung test, we assume that the unit-root procedure is homogeneous. The Im–Pesaran–Shin test examines the presence of cross-section dependence in the unit-root procedure.
[18] See Moreno and Vayá (2002) for a very extensive explanation.
[19] Cliff and Ord (1981) confer this statistic with an advantage over the other spatial dependence indices.

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close to -1[20]. Notably, the results of the spatial dependence analysis are used as an indicator of the BWE on the individuals' decision to participate in the labor market, namely, the AWE and the DWE are also the result of a social effect associated with the behavior observed in the environment.

5. Results

The first part of this section shows the estimated effects of the business cycle on the LPR in the Spanish provinces. Second, we test the existence of the BWE as a positive spatial correlation in the cyclical sensitivity of the LFP among the Spanish NUTS-3 units.

5.1. Results for the AWE and the DWE

For this research, we require information on the unemployment rate and the LFP. We used data from the Labor Force Survey (Encuesta de Población Activa, EPA) conducted by the National Statistics Institute for the 50 Spanish provinces (NUTS-3) in the period 1977–2015 (table A2 in Appendix 3 provides detailed information on the variables).

Table 2 exposes the results of estimating equation (5) when the cyclical components of the variables are obtained by the application of the HP filter with λ=400. Additionally, and because of the length of the period, we analyze what occurs in two shorter periods: 1977–1996 and 1997–2015. In this manner, we test more precisely the

[20] The existence of positive spatial dependence means that areas with high (low) values of the target variable are surrounded by other areas that also display high (low) values for said variable. Negative spatial dependence indicates that the areas with high (low) levels in the variables studied are located close to other territories where said variable displays low (high) values.

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effect of the business cycle over the LFPRs in Spain and the robustness of the results. There are three main reasons to split the full period into these two sub-periods. First, each of these two sub-periods represents, approximately, a complete business cycle. Second, in the last years of the nineties, Spain experienced a large wave of immigration (Carrasco et al. 2008) that generated notable changes in the economic dynamics of the Spanish labor market (Farré et al. 2011). Third, the length of these two sub-periods is approximately equal (20 and 19 years, respectively). Columns 2 and 3 in table 2 present the estimations of these sub-periods.

The results show 22 statistically significant coefficients for the period 1977–2015, and the DWE prevails over the AWE in nineteen of them. In the first sub-period (1977–1996), 27 provinces present statistically significant results, and the DWE is the most relevant effect. The AWE is present only in four territories. For the second sub-period (1997–2015), seven provinces show statistically significant results, and the DWE is the predominant effect in four of them.

To test the robustness of the results, we re-estimate the sensitivity of the LFP with the cyclical components obtained by using the QT procedure and the HP filter with $\lambda = 100$ (table A3 in Appendix 3). For the whole period, the results are similar to those obtained before, with many statistically significant results, especially when we employ the QT procedure. The principal effect is the DWE, which is present in 30 out of the 34 provinces that have statistically significant results. For the two sub-periods, the DWE also predominates in most of the provinces where the results are statistically significant. We only found the AWE in Lugo and Corunna (A) between 1977 and 1996 and in Palencia, Caceres and Huelva between 1997 and 2015. In the case of the HP filter with $\lambda=100$, we

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obtain the same results. The DWE also predominates for the whole period and for the first sub-period.

Figure A2 in Appendix 3 includes two scatterplots that confirm the robustness of the estimations. The results obtained by the HP filter with $\lambda = 400$ and $\lambda = 100$ are positively correlated with an R^2 equal to 0.85 and a correlation coefficient (ρ) of 0.92. Additionally, the same pattern is maintained when we observe the relationship between the estimations of the HP $\lambda = 400$ and the QT procedure; in this case, the R-squared is 0.79, and ρ is 0.89.

5.2. Spatial analysis of the cyclical sensitivities

We have estimated the cyclical sensitivities. Now, we study whether there is a social influence in our results. The theoretical model suggested that the PR cyclical pattern of a specific area is positively related to the cyclical pattern shown in the PRs of neighboring areas. This effect, named BWE, may be easily tested by means of spatial econometric techniques in line with those expressed in equation (4). To begin the analysis, we must establish a neighborhood criterion such as the k-nearest neighbors (Knn) or the inverse distance (ID)[21]. To achieve the goal of this paper, we determine that ID and nearest neighbor are the appropriate spatial weight matrices because part of the contribution of this research is to test if the social effect is weaker when spatial proximity is less evident. The advantage of these two types of spatial matrices is that we can graduate spatial proximity in a continuous manner. In addition, the distance matrix enhances the

[21] See O'Sullivan and Unwin (2010) for more detailed information about the Knn and ID matrixes.

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importance of proximity with less weight to farther locations (Bertinelli and Nicolini 2005). It is true that, by using contiguity spatial matrices, we can define the first-order neighborhood, second neighborhood, and so forth; however, we conclude that this is insufficiently continuous. Moreover, we have islands in our database, causing the well-known drawbacks of the contiguity spatial matrices. Notably, we did not use socioeconomic weight matrices because our phenomenon has a clear spatial rationale. In this paper, we use ten different Knn matrices ($K = 1 \dots 10$) where the specification of the spatial weights is

$$SW_{i,j} = \begin{cases} 1, & if\ centroid\ of\ j\ is\ one\ of\ the\ k\ nearest\ centroids\ to\ that\ of\ i \\ 0, & otherwise \end{cases}$$

We also apply ten ID matrices for different values of α ($\alpha = 3, 2.75, \dots 0.75$) and the following spatial weights:

$$SW_{ij} = \begin{cases} d_{ij}^{-\alpha}, & if\ i \neq j \\ 0, & otherwise \end{cases}$$

where α is any positive parameter, and $d_{i,j}$ is the distance between regions i and j.

Table 3 presents the results of Global Moran's I for the cyclical sensitivity of the LFP obtained with the HP method with λ=400[22]. For the period 1977–2015, the results show a positive spatial dependence with both sets of matrices. The analysis of the sub-

[22] We also perform the same analysis by putting a value equal to 0 in those provinces where we have obtained results of the cyclical sensitivities that are not statistically significant (no prevalence of either the AWE or the DWE over the other in these territories). The results are very similar to what we present in table 3. Detailed results are available from the authors upon request

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periods indicates that between 1977 and 1996, a positive spatial dependence is observed either when we consider less than three neighbors or when the distance is more penalized. From 1997 to 2015, a positive spatial dependence is again observed for all the matrices, but it is weaker than in the case of the whole period. Additionally, a test to detect local spatial dependence is implemented. The local Moran's I statistic and two neighboring matrices are used: five nearest neighbors and ID with $\alpha = 1$. The results show a higher concentration of DWE in the northeast of Spain, whereas the AWE is more common in the east and south (figure A3 in Appendix 3).

To test the robustness of our results, we perform the spatial analysis using the values obtained by the QT procedure and the HP filter with $\lambda = 100$ (table A4 in Appendix 3). In the case of the QT procedure, the results show positive spatial dependence both for the whole period and for the two sub-periods. This effect is stronger than before and occurs for the two sets of spatial matrices. If we use the HP filter with λ=100, the results are similar to those obtained with λ=400. The spatial dependence is present both for the entire period and for the two groups of matrices. The analysis by sub-periods only shows spatial dependence between 1997 and 2015 and for some spatial matrices. Figures 2 and 3 present the scatter plots of Global Moran's I for the HP filter (λ=400) when three Knn matrices (K=1, 3 and 5) and three ID matrices (α=1, 2 and 3) are used. The spatial correlation that is present in figures 2 and 3 is consistent with the interaction presented in figure 1 and allows us to confirm the presence of the BWE. This corroborates the existence of a social effect, which causes the cyclical sensitivity of the LFP in one territory to be influenced by what occurs in its neighboring regions[23].

[23] Detailed results for the other spatial matrices and the other two methods (QT procedure and HP (λ=100)) are available from the authors upon request.

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The next step in the spatial analysis is to study the evolution of the spatial dependence before changes in neighborhood parameters. As explained, each neighborhood criterion includes ten different levels. Depending on the spatial correlation at each level, we can understand how the social effect works. The results in table 3 show that as we increase the number of neighbors (or we reduce the α parameter), the spatial correlation coefficient decreases. To explain this point in more detail, figures 4 and 5 depict the evolution of the spatial correlation as the matrix parameters of the two sets change. The decreasing slope in both figures indicates that the BWE is caused by what occurs in the nearest territories. As we increase the number of provinces that we consider neighbors, the social effect tends to disappear[24].

6. Extensions

The results presented in Section 5 have demonstrated the existence of a BWE; thus, we must broaden the analysis to discard other possible explanations. To this end, two spatial models are presented that allow us to confirmation of the influence of the closest environment and global spillovers, from a geographical point of view, over the cyclical sensitivity of the PR. Appendix 2 also includes a sensitivity analysis with specifications that control for population composition, methodological changes, labor reforms, or data structure.

[24] Detailed results for the other two methods (QT procedure and HP with λ=100) are available from the authors upon request.

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Regarding cross-sectional dependence, a logical assumption is that the correlation should be related to the variables not included in the model and would be detected by estimating an SEM such as that presented in equation (7):

$$CPR_{it} = \alpha + \beta_{i1} \cdot CUR_{it} + \beta_2 D_{2001} + \mu_i + \varepsilon_{it} \tag{7}$$

$$\varepsilon_{it} = \lambda W \varepsilon_{it} + \eta_{i,t} \;\; with \;\; \eta_{i,t} \sim N\left[0. \sigma_\eta^2 I_n\right]$$

From the results obtained in this new estimation, the spatial correlation of the cyclical sensitivity is tested again with the two previous weight matrices (ID and five nearest neighbors). The results presented in figure 6 show that the spatial correlation decreases slowly. However, a statistically significant BWE is maintained even when spatial dependence in the errors is also detected (table A5 in Appendix 3 includes the cyclical sensitivity coefficients and the lambda parameter related to the SEM).

The second spatial approach is the spatial lag model or spatial autoregressive model (SAR). This model is a global spillover specification that includes an additional term obtained as the product of the spatial weight matrix and the cyclical component of the PR, in equation (8):

$$CPR_{it} = \alpha + \rho WCPR_{it} + \beta_{i1} \cdot CUR_{it} + \beta_2 D_{2001} + \mu_i + \varepsilon_{it} \tag{8}$$

In this case, because of the presence of the spatial lag of the dependent variable, a change in a single observation (region) associated with any given explanatory variable affects the region (direct impact) and potentially affects all other regions indirectly (indirect impact). The total effect is the sum of both the direct and the indirect or global

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effect and is obtained as $\beta_{i1}(1-\rho W)^{-1}$. When the global spatial correlation test over that total effect is performed, the Moran I is not significantly different from 0 (figure 7). This result makes sense because the SAR model captures the global spillovers and the spatial lag coefficient of the dependent variable is positive and significant (table A5 in Appendix 3 includes the total effects of changes in CUR variables and the rho parameter)[25].

The similarity in magnitude and significance of ρ and λ seems to indicate that the spatial correlation was included in the disturbance of the SEM (LeSage, 2014). If we add to this that the spatial dependence on the cyclical sensitivity is still present when estimating the SEM and disappears with the SAR model, we consider that the latter is the true data-generating process. These results, and especially the value of the ρ parameter in the SAR model, confirm the presence of global spatial dependence (LeSage and Pace, 2009; García-López et al., 2020; Lopez-Torres et al., 2017) and therefore also the BWE hypothesis.

7. Discussion and policy implications

We have offered empirical evidence of the existence of the BWE; thus, in the following paragraphs, we propose economic policy implications. We organize the economic policy implications and recommendations into three categories: proposals related to the heterogeneity in the cyclical response of the LFP in different spatial units; economic policy consequences related to the spatial dependence in the LFP cyclical patterns (i.e.,

[25] As an additional measure of robustness, we have estimated a Spatial Durbin Model that includes the spatial lag in the cyclical component of the unemployment rate; once again, the rho parameter was positive and significant (results are available upon request of the authors).

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the significance of the BWE); and policy suggestions resulting from the particular administrative hierarchy among NUTS-2 and NUTS-3 units in Spain.

First, our results show that local labor markets react differently to cyclical fluctuations. More precisely, we find that in some Spanish NUTS-3 units, the DWE dominates the AWE; in other units, the AWE is stronger than the DWE; and there are spatial units where both effects offset each other. In general, the economic measures should be conducted while considering the territorial context; thus, policymakers should not design economic policies that have the same intensity of effect in all regions. In other words, different territories require policies tailored to the labor market dynamics of each territory. More specifically, this spatial heterogeneity has implications for the implementation of both aggregate demand policies and policies on the supply side.

As aforementioned, during a downturn, if the DWE dominates the AWE, the unemployment rate is understated, whereas if the AWE prevails over the DWE, the unemployment rate is overstated. Evidently, the opposite is true during an economic upturn. Hence, an obvious economic policy implication of our results is that in those geographical areas in which we have estimated a prevailing DWE, economic authorities ought to implement a more expansionary fiscal policy (e.g., government spending increases or tax cuts) than indicated by the official unemployment rate during a recession. Following the same line of reasoning, but from an aggregate supply perspective, additional active labor market policies (e.g., training schemes, public employment services) should be applied in those spatial units with a predominant DWE during downturns, and vice versa. In addition, our estimates of the Spanish spatial units with a prevailing DWE or AWE serve as a guideline for policymakers to better distribute

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a limited fiscal budget in different business cycle phases. Policymakers should devote less (more) budgetary resources to spatial units with a predominant AWE during recessions (expansions) than suggested by the measured unemployment rate and more (less) to those with a prevailing DWE. This economic policy rule would enhance efficiency as long as the fiscal budget remained unchanged at the aggregate level.

Second, our evidence shows a significant spatial dependence in the cyclical sensitivity of LFP, that is, what we name the BWE. Thus, cyclical patterns that the labor force follows in a given territory are guided and conditioned by the behavior of its neighboring territories. For this reason, it is necessary to consider this social effect when analyzing the policy implications of the labor market policies. For instance, the implementation of macroeconomic policies by the regional governments could cause spillover effects beyond those initially expected. The obvious economic policy implication regarding this topic is that regions cannot be studied in isolation from each other but interact with their neighbors. However, this statement is too general.

A more specific economic policy implication regarding the influence of the BWE is that the policies implemented should pay more attention to the existence of spatial areas rather than single spatial units to better understand the relationship between the labor market participation and the state of the business cycle. If the BWE is a relevant socioeconomic phenomenon, we might expect the DWE and the AWE to spread across neighboring spatial units during economic upturns and downturns. In this manner, the overstatement or understatement of true unemployment across spatial units would be contagious, and consequently, the correct economic policy; even more importantly, the

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correct intensity of such a policy should be determined by adopting a supra-provincial perspective.

The last group of economic policy implications is related to the particular administrative division of the Spanish territory NUTS-3 units in Spain (provinces), which are grouped into NUTS-2 units (autonomous communities) in some cases but not in others. Thus, in a limited number of cases (Madrid, Balearic Islands, Asturias, Cantabria, Rioja (La), Murcia, and Navarre), a coincidence is observed between the NUTS-2 and NUTS-3 levels, but this does not occur in the remaining 43 Spanish provinces. Furthermore, our findings imply that the actions of the regional governments at the NUTS-2 level could affect either other NUTS-2 territories or NUTS-3 units that do not belong to that region. More importantly, Spanish NUTS-2 units manage a significant portion of the government's budget, whereas NUTS-3 units run much less of it[26]. This entails the autonomous communities playing a key role from an economic and political point of view, and the Spanish provinces have a limited capacity to act. As our results point to a strong interdependence at the NUTS-3 level, coordination of economic policies among neighboring NUTS-2 regional governments is required because there are critical spillover effects beyond the NUTS-2 level administrative division.

The aforementioned issue could be addressed from two points of view. First, political leaders governing neighboring autonomous communities might spontaneously seek higher coordination in their policies against unemployment. In this vein, supra-regional committees managing labor market policies could be created to coordinate

[26] Spanish NUTS-2 (autonomous communities) represented approximately 30% of public expenditure in Spain during 2015 and 2016. NUTS-3 units (provinces) was approximately 11% of public spending in Spain during those same years (OECD, 2017).

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political efforts to minimize the true unemployment problem, by devising strategies that account for the spillover effects. Second, if regional (NUTS-2) governments do not reach an agreement by themselves, the Spanish central government might act to promote such an agreement. Here, again, there are two options: (1) the Spanish central government might create by itself an inter-regional committee where the representatives in charge of labor issues in each autonomous community could hold discussions with other regional representatives to make agreements that seek the coordination; and (2) the Spanish central government might directly act to solve this question. More precisely, it could create a political institution that depends on the Ministry of Labor (e.g., a Secretary of State or a General Directorate), devoted exclusively to coordinating different regional labor market policies[27].

8. Conclusions

The main purpose of this paper is to test whether the relationship between the business cycle and LFP in any given area is affected by the behavior of its neighbors. To achieve this objective, we first elaborate a microeconomic decision model to conceptualize the AWE and the DWE. In a second stage, using an aggregation process, we incorporate the BWE as a social effect. Finally, we use spatial econometrics techniques to test for the existence of the BWE in Spanish local labor markets.

The first part of this work studies the cyclical sensitiveness of the LFP by employing a panel dataset composed of the 50 Spanish provinces during the period

[27] Coordination among different actors is proposed, but in practice this could be quite challenging. A main consideration is thus how feasible this would be (e.g. coordination failure, transaction costs, and so on and so forth). These issues might be included within the scope of the political economy and constitute an appealing avenue for future research.

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1977–2015. Additionally, because of the length of the period of study, we extend our analysis to two sub-periods (1977–1996 and 1997–2015). Regardless of the method used to obtain the cyclical components of the variables (HP with λ =400, HP with λ =100, or QT), we conclude that the DWE dominates in most of the territories and in periods where the coefficients are significant.

Our theoretical model demonstrates that the cyclical sensitivity of the LFP in one area is influenced by the behavior of its neighbors. To study that finding, after conducting a macroeconomic aggregation process, we coined the BWE and tested it with standard spatial econometric techniques we derived directly from our theoretical discussion. Using different neighborhood criteria, the results reveal the presence of a positive global spatial dependence in the cyclical sensitivity of the LFP in the Spanish local labor markets. This is consistent with what we illustrate in our theoretical framework and verifies the existence of the BWE. Finally, the empirical analysis shows that the intensity of the BWE is not linear, that is, as we fix a laxer neighborhood criterion, the strength of the BWE decreases.

Based on our work, we propose economic policy implications that affect the outcome of the regional labor markets. First, policymakers should consider that the regions may react differently to the economic shocks of the business cycle. Thus, the policies should be applied while considering the economic dynamics of each zone because the application of economic policy with the same intensity for all the regions could lead to heterogeneous results. Another notable factor is that the territories interact with their neighbors; thus, they are not fully independent of each other. In this manner, policymakers should focus on spatial areas instead of spatial units because of the

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existence of social effects among the territories that might condition the outcome of the economic policies. Our work corroborates that social effects play a key role in implementing labor market policies. This implies that these phenomena could generate types of effects that are not initially planned and that affect the economic dynamics of neighboring areas, even when the neighbors belong to a different territorial administration. That interdependence at the NUTS-3 level requires coordination of the economic policies among neighboring NUTS-2 regional governments.

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APPENDIX 1: Theoretical model

In this appendix, we develop the theoretical framework to define the BWE. Non-critical Assumptions 1–6 of the model are as follows:

Assumption 1. *Labor is homogenous. This implies that the wage is the same for all workers*[28]*.*

Assumption 2. *Labor contracts last one period. To sign a new contract, it is always necessary to spend a fixed amount of time in job-search activities, as specified in Assumption 3.*

Assumption 3. *A certain amount of time is associated with labor participation. Before signing a new contract, the worker must devote s units of time to job searches. Here, s is considered a fixed and exogenous sum of time*[29]*.*

Assumption 4. *A positive unemployment rate exists. Such a rate determines the likelihood p of finding a job, which is the same for all individuals*[30]*.*

Assumption 5. *The size of the working week, which we denote by $\bar{l}$, is fixed and exogenously determined*[31]*.*

Assumption 6. *The utility function is additive. That is, if we denote C as the consumption (or the total income because there is no saving) and H as the leisure time (i.e., total time minus hours of work), this assumption establishes that*

[28] This assumption is adopted because of the macroeconomic orientation of the paper.

[29] It is beyond the scope of the paper to consider s an endogenous variable. That is the field of job-search theory. This theory was pioneered by Mortensen (1970) and McCall (1970). See Lippman and McCall (1976a), Lippman and McCall (1976b), Mortensen (1986), and Mortensen and Pissarides (1999) for some classical surveys on the topic. Recent examples of this type of literature are Tatsiramos and van Ours (2012) and Tatsiramos and van Ours (2014).

[30] In other words: unemployment is primarily involuntary. Obviously, the higher the unemployment rate, the lower the p.

[31] We are interested in the extensive margin of the labor supply, and this assumption allows us to focus on the participation decision.

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$U(C, H) = \Lambda(C) + \Omega(H)$. *As usual, marginal utilities are supposed to be positive and decreasing*[32].

The set of alternatives for the worker is shown in Figure A1 (Appendix 3). Inside the utility function, the levels of consumption and leisure have been replaced by the corresponding values associated with each decision. In this manner, we are already considering the budget constraints within the choice framework. In Figure A1, w is the real wage per unit of time, $\bar{l}$ stands for the duration of the fixed working week, y is the real non-labor income, and s stands for the job-search duration linked to the participation decision. Total time has been normalized to 1.

According to Figure A1, an individual has two options. Each of these options is associated with a level of utility, either certain or expected: (A1) not to participate and (A2) to participate, which can be formalized, respectively, as

$$U(y, 1) \quad (A1)$$

$$pU(w\bar{l} + y, 1 - \bar{l} - s) + (1 - p)U(y, 1 - s) \quad (A2)$$

The reservation wage for an individual (w^R) might be defined, as per usual, as the value of w that equates both options. We easily prove from expression (A3) that w^R is always positive ($w^R > 0$)[33]:

$$pU(w^R\bar{l} + y, 1 - \bar{l} - s) + (1 - p)U(y, 1 - s) = U(y, 1) \quad (A3)$$

[32] This assumption is less restricting than it initially seems. Firstly, this sort of utility function generates indifference curves that typically decrease and are convex to the origin. Secondly, within the ordinal utility theory, a logarithmic transformation of the very well-known Cobb–Douglas utility function is additive, representing an identical set of preferences.

[33] Focusing first on leisure time, we have $1 > (1 - s) > (1 - \bar{l} - s)$. This would entail that $w^R \, \bar{l} > y$ in order to attain an equality in (A3), which implies that $w^R > 0$.

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If workers have different preferences regarding consumption–income and leisure–work and different non-labor incomes, their reservation wages will also differ. This diversity of reservation wages $w^R \in [0, +\infty)$ might be represented by a cumulative distribution function $\phi(\cdot)$. If the remainder of the PR determinants do not change (i.e., non-labor income and likelihood of finding a job in our theoretical setting), the aggregate labor supply could be expressed in formal terms accordingly:

$$L = N \cdot \phi(\cdot) \qquad (A4)$$

where L denotes the labor force, and N denotes the total working-age population. Therefore, the PR is simply $\phi(\cdot)$, as expressed in equation (A5):

$$PR = \frac{L}{N} = \phi(\cdot) \qquad (A5)$$

Inasmuch as $\phi(\cdot)$ is a cumulative distribution function, by definition, that proportion is increasing in its argument, $\phi_w > 0$. Nevertheless, as we show next, non-labor income and the likelihood of finding a job play a critical role in determining PR because both change. To incorporate this idea, we call w_M^R the reservation wage for the median individual within the cumulative distribution. In this manner, a stylized PR function is described by means of expression (A6):

$$PR = \phi(w, w_M^R) \qquad (A6)$$

As aforementioned, $(\partial PR/\partial w) > 0$, by definition; furthermore, it is consistent with the concept of a reservation wage $(\partial PR/\partial w_M^R) < 0$. Finally, w_M^R is thus a function of some additional arguments. In the model developed here, w_M^R depends on y and p. In

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addition, $y(Z)$ and $p(Z)$ are regarded as functions of the business cycle (Z). We consider that if our measure of the business cycle increases, the state of the economy improves, whereas when Z decreases, the economy worsens. Thus, we may rewrite expression (A6) as follows[34]:

$$PR = \phi(w, w_M^R[y(Z), p(Z)]) \tag{A7}$$

Equation (A7) reveals that PR depends on the business cycle through a double channel: cyclical variations in the median worker's non-labor income that result in the AWE, and cyclical changes in the likelihood of finding a job that results in the DWE.

As aforementioned, the driver of the AWE is one spouse's non-labor income variations as a result of the other spouse's changes in his/her labor market status. We easily demonstrate that this result fits well in our theoretical framework. We first create an implicit function $R(\cdot) = R(w_M^R, y, p, \bar{l}, s)$ from equation (A3), which is defined by the following expression:

$$R(\cdot) = pU(w_M^R\bar{l} + y, 1 - \bar{l} - s) + (1 - p)U(y, 1 - s) - U(y, 1) = 0$$

and then, we use the implicit function theorem:

$$\frac{\partial w_M^R}{\partial y} = -\frac{\partial R/\partial y}{\partial R/\partial w_M^R} = -\frac{pU_C(w_M^R\bar{l} + y) + (1 - p)U_C(y) - U_C(y)}{p\bar{l}U_C(w_M^R\bar{l} + y)} > 0 \tag{A8}$$

[34] The basic exposition of this aggregation process may be found in some labor economics' textbooks (e.g., Boeri and van Ours, 2013; Cahuc and Zylberberg, 2004; Cahuc et al. 2014). The idea of the cumulative distribution function $\phi(\cdot)$ is from Cahuc and Zylberberg (2004). The idea of the PR function depending on the reservation wage of the median individual, which depends on the business cycle, is ours.

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It is evident that a reduction in the non-labor income (as a consequence of a downturn) would decrease the reservation wage of the median worker, and this would encourage labor participation. In more formal terms (maintaining p constant), we may characterize the AWE by means of (A9):

$$\left.\frac{\partial PR}{\partial Z}\right|_{\bar{p}} = \frac{\partial PR}{\partial w_M^R} \cdot \frac{\partial w_M^R}{\partial y} \cdot \frac{\partial y}{\partial Z} < 0 \qquad (A9)$$

because we know that $\partial y/\partial Z > 0$ (by hypothesis), that $\partial w_M^R/\partial y > 0$ (from the discussion in this section), and that $\partial PR/\partial w_M^R < 0$ (from the concept of reservation wage).

As explained, the DWE operates through changes in expectations of finding a job. Hence, the method to formalize the DWE within the model is by means of p. Taking equation (A3) and making use again of the implicit function $R(\cdot) = R\left(w_M^R, y, p, \bar{l}, s\right)$, we straightforwardly compute the effects of changes in p on w^R:

$$\frac{\partial w_M^R}{\partial p} = -\frac{\partial R/\partial p}{\partial R/\partial w_M^R} = -\frac{U\left(w_M^R\bar{l} + y, 1 - \bar{l} - s\right) - U(y, 1 - s)}{p\bar{l}U_C\left(w_M^R\bar{l} + y\right)} < 0 \qquad (A10)$$

The negative sign of (A10) is the result of the definition given in (A3). First, obviously, $U(y, 1) > U(y, 1 - s)$. Second, to achieve equality in (A3), $U\left(w_M^R\bar{l} + y, 1 - \bar{l} - s\right) > U(y, 1) > U(y, 1 - s)$ must be fulfilled. In other words, when p rises (drops), w_M^R decreases (increases). We can obtain a stylized mathematical version of the DWE (maintaining non-labor income constant) through expression (A11):

$$\left.\frac{\partial PR}{\partial Z}\right|_{\bar{y}} = \frac{\partial PR}{\partial w_M^R} \cdot \frac{\partial w_M^R}{\partial p} \cdot \frac{\partial p}{\partial Z} > 0 \qquad (A11)$$

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As before, we can affirm that $\partial p/\partial Z > 0$ (by hypothesis), that $\partial w_M^R/\partial p < 0$ (from the discussion in this section), and that $\partial PR/\partial w_M^R < 0$ (from the concept of reservation wage).

We have described the two theoretical effects separately; now, we analyze their effects jointly. When, for instance, the economy enters a recession, the PR decreases as a consequence of the DWE and increases because of the AWE. What may be observed directly through the data is the net effect, namely, the sign of (A12):

$$\frac{\partial PR}{\partial Z} = \underbrace{\frac{\partial PR}{\partial w_M^R}}_{(-)} \left(\underbrace{\frac{\partial w_M^R}{\partial y} \cdot \frac{\partial y}{\partial Z}}_{AWE(+)} + \underbrace{\frac{\partial w_M^R}{\partial p} \cdot \frac{\partial p}{\partial Z}}_{DWE(-)} \right) = \beta^* \gtreqless 0 \qquad (A12)$$

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Appendix 2: Sensitivity analysis.

Population composition effect.

The first point to consider when explaining the observed spatial dependence is the possible influence of the population characteristics in each territory. To analyze this effect, four additional variables are included in equation (5) to indicate the composition by gender and age in each territorial unit. The new model is expressed as follows:

$$CPR_{it} = \alpha + \beta_{i1} \cdot CUR_{it} + \beta_2 D_{2001} + \beta_3 F + \beta_4 A1 + \beta_5 A2 + \beta_6 A3 + \mu_i + \varepsilon_{it} \quad (A13)$$

Where the F variable is the weight of females and variables $A1, A2$, and $A3$ show the percentage of individuals aged from 15 to 24 years, from 25 to 54 years, and from 55 to 64 years, respectively, over the total population. Once the estimation is complete, the presence of spatial correlation is also tested using, as spatial weight matrices, the 5nn and the ID with $\alpha = 1$.

The results presented in figure A4 show that the spatial dependence in the cyclical sensitivity is maintained, although with somewhat lower values of the Moran's I. This finding seems to indicate that the BWE is not a consequence of similar population structures in bordering territories (the cyclical sensitivity coefficients are included in table A5).

To deepen the demographic aspects, the cyclical sensitivity of the activity rate is also estimated separately for males and females (table A5). In this case, the spatial correlation is only present for women and with values of the Moran's I higher than those obtained previously (figure A5 and A6). This result is coherent with the social effects

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found in the labor supply of women by Woittiez and Kapteyn (1998) or Maurin and Moschion (2009).

Methodological changes and labor reforms.

Other important aspect when analyzing a long series of data is the possibility of methodological changes or reforms that may cause breaks in series. Regarding methodological changes, the EPA presents three important modifications that may affect our sample and that occurred in 1999, 2001, and 2005 (the 2001 change was considered in previous specifications because of its special relevance). As for labor reforms, Spain is characterized as having frequent legislative changes that affect the labor market. However, the most ambitious reforms since the approval of the Workers' Statute (1980) were implemented in 1984, 1994, 2010, and 2012. To consider all these possible effects, we include eight dummy variables in the model (equation A14).

$$CPR_{it} = \alpha + \beta_{i1} \cdot CUR_{it} + \beta_2^1 D_{1980} + \beta_2^2 D_{1984} + \beta_2^3 D_{1994} + \beta_2^4 D_{1999} + \beta_2^5 D_{2001} + \beta_2^6 D_{2005} + \beta_2^7 D_{2010} + \beta_2^8 D_{2012} + \mu_i + \varepsilon_{it} \qquad (A14)$$

Where each D_i represents the methodological change or labor reform made in year i. We have estimated equation A14; now, the global spatial correlation test on the β_{i1} is repeated using the ID and the five nearest neighbors matrix. The results of this analysis are presented in figure A7 and once again reaffirm the robustness of our conclusions with a statistically significant BWE (the estimated values for the cyclical

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sensitivity are shown in table A5 of Appendix 3). The methodological changes and labor reforms have a significant effect on the PR but do not explain the spatial correlation of the cyclical sensitivity.

Quarterly data.

Finally, we analyze if spatial dependence is determined by data structure. Thus, we re-estimate equation 5 by using quarterly data. Using this type of data has additional consequences. On the one hand, it is necessary to deseasonalize the time series, and to do that, we use the x-12 ARIMA method. On the other hand, to obtain the cyclical component of the series, we must modify the smoothing parameter of the HP filter. The empirical literature on this issue is unanimous and advises using λ=1600 (Ravn and Uhlig, 2002). The model also includes a three lags structure for the dependent variable and the independent variables. In this manner, two objectives are achieved: the results are comparable with the yearly structure used in the rest of the work, and adjustments that need more than one quarter to take effect are considered. The correct specification in this case is as follows:

$$CPR_{it} = \alpha + \sum_{j=1}^{3} \psi_i^j CPR_{it-j} + \beta_{i1} \cdot CUR_{it} + \sum_{j=1}^{3} \beta_{i1}^j CUR_{it-j} + \beta_2 D_{2001} + \mu_i + \varepsilon_{it} \qquad (A15)$$

Including a lag structure in the dependent variable and in the explanatory variables provides two types of cyclical sensitivity: short term (β_i^S) and long term (β_i^L). They are defined as follows:

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$$\beta_i^S = \beta_{i1} + \sum_{j=1}^{3} \beta_{i1}^j \quad \text{and} \quad \beta_i^L = \beta_i^S / (1 - \sum_{j=1}^{3} \psi_i^j) \qquad (A16)$$

In this point, the spatial correlation of β_i^S and β_i^L is tested again to analyze if the data structure modifies the results. As in the previous cases, the spatial dependence is maintained with both matrices (five nearest neighbors and ID), which confirms that the yearly data structure does not determine the presence of the BWE. We can also check that the value and the significance of the Moran's I are similar in the sensitivity of the short term and long term (figures A8 and A9)[35].

[35] Table A5 in Appendix 3 presents the short- and long-term elasticities obtained from the quarterly data estimation.

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Appendix 3: Tables and figures

Table A1. Unit-Root tests

	HP (λ=400)		QT		HP (λ=100)	
	CPR	CUR	CPR	CUR	CPR	CUR
IPS	-11.930***	-6.254***	-6.330***	-1.817**	-15.745***	-9.008***
LLC	-9.812***	-12.947***	-1.694**	-5.787***	-16.330***	-16.402***
HT	0.551***	0.756***	0.705***	0.872***	0.647***	-14.723***
B	-10.121***	-9.917***	-5.945***	-2.891***	-14.391***	-4.387***

Notes: IPS is the W-t-bar statistic for Im–Pesaran–Shin unit-root test (panel-specific AR parameter, panel means included and without time trend); LLC refers to the bias-adjusted t statistic for Levin–Lin–Chu unit-root test (1 lag in the ADF); HT is the rho statistic for the Harris–Tzavalis test (common AR parameter, panel means included and without time trend) and finally, B refers to lambda statistic for the Breitung unit-root test (common AR parameter, panel means included, and without time trend). ***, **, and * show statistical significance at 1%, 5%, and 10% levels, respectively.

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Table A2. Descriptive statistics

	Variables	Periods	Mean	Std. Dev.	Min	Max
HP (λ=400)	CPR	1977-2015	4.98e-10	1.277	-5.539	3.967
		1977-1996	-4.98e-10	1.170	-3.960	3.774
		1997-2015	4.57e-10	1.258	-5.561	3.610
	CUR	1977-2015	2.07e-09	3.451	-11.377	9.376
		1977-1996	1.31e-09	2.576	-7.987	10.234
		1997-2015	1.17e-09	3.851	-10.698	10.000
QT	CPR	1977-2015	-5.93e-09	1.590	-6.263	5.500
		1977-1996	-0.120	1.380	-3.972	4.806
		1997-2015	0.126	1.776	-6.263	5.500
	CUR	1977-2015	-9.39e-09	5.426	-16.482	13.693
		1977-1996	1.528	4.283	-12.300	12.359
		1997-2015	-1.608	6.008	-16.482	13.693
HP (λ=100)	CPR	1977-2015	1.56e-08	1.080	-5.374	3.348
		1977-1996	0.009	1.068	-3.831	3.348
		1997-2015	-0.010	1.093	-5.374	3.227
	CUR	1977-2015	-1.01e-07	2.693	-9.784	8.980
		1977-1996	0.239	2.447	-8.003	8.980
		1997-2015	-0.251	2.909	-9.784	7.708

Notes: CPR is the cyclical component of the PR. CUR is the cyclical component of the unemployment rate.

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Table A3. Cyclical sensitivity of the LFP (QT procedure and HP λ=100)

	QT			HP=100		
	1977–2015	1977–1996	1997–2015	1977–2015	1977–1996	1997–2015
Alava	-0.286***	-0.342***	-0.257***	-0.013	-0.186	0.175
Albacete	0.003	-0.001	-0.002	0.025	-0.012	0.048
Alicante	-0.045	-0.071	-0.041	-0.108*	-0.292***	0.020
Almeria	-0.177***	-0.263***	-0.153***	-0.067	-0.427***	0.042
Asturias	-0.011	0.096	-0.055	0.055	0.015	0.083
Avila	0.015	0.055	0.003	0.062	0.064	0.070
Badajoz	-0.063*	-0.152***	-0.020	0.020	-0.110	0.150*
Balearic Islands	-0.159***	-0.232***	-0.129*	0.011	-0.135	0.101
Barcelona	-0.125***	-0.082*	-0.182***	-0.009	-0.033	0.030
Burgos	-0.220***	-0.179**	-0.245***	-0.084	-0.119	-0.035
Caceres	0.087**	0.036	0.105**	0.138***	-0.094	0.200***
Cadiz	-0.013	-0.024	-0.006	0.068	0.089	0.060
Cantabria	-0.196***	-0.138*	-0.231***	-0.113	-0.111	-0.109
Castellon de la Plana	-0.179***	-0.188**	-0.189***	-0.119**	-0.277***	-0.046
Ciudad Real	-0.101**	-0.086	-0.109*	-0.027	-0.064	0.021
Cordoba	-0.017	-0.068	0.001	0.033	-0.167**	0.142**
Corunna (A)	-0.005	0.289***	-0.149*	0.239***	0.439***	0.039
Cuenca	-0.038	-0.043	-0.040	-0.032	-0.205	0.030
Girona	-0.334***	-0.442***	-0.285***	-0.220***	-0.415***	-0.075
Granada	-0.025	-0.085	-0.004	0.006	-0.154*	0.087
Guadalajara	-0.204***	-0.167***	-0.239***	-0.130*	-0.250***	0.009
Guipuzcoa	-0.251***	-0.193***	-0.311***	-0.089	-0.037	-0.216
Huelva	0.050	-0.014	0.078*	0.100**	-0.129*	0.260*
Huesca	-0.215***	-0.083	-0.305***	-0.001	0.076	-0.057

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Jaen	0.012	-0.068	0.051	0.020	-0.080	0.142**
Leon	0.001	0.037	-0.016	0.034	-0.173	0.126
Lleida	-0.326***	-0.118	-0.405***	-0.053	0.040	-0.100
Lugo	0.143**	0.326**	0.106	0.154	0.523***	0.024

Table A3(continuation)

	QT			HP=100		
	1977–2015	**1977–1996**	**1997–2015**	**1977–2015**	**1977–1996**	**1997–2015**
Madrid	-0.242***	-0.132**	-0.321***	-0.071	-0.058	-0.082
Malaga	0.047	0.063	0.033	0.026	0.003	0.043
Murcia	-0.146***	-0.194***	-0.138***	-0.056	-0.219**	0.055
Navarre	-0.286***	-0.193***	-0.388***	-0.110	-0.142	-0.060
Orense	-0.074	-0.403***	-0.013	-0.088	-0.671***	0.050
Palencia	0.094**	0.048	0.107*	0.049	-0.035	0.207*
Palmas (Las)	-0.098***	-0.085*	-0.112**	-0.099**	-0.438***	0.035
Pontevedra	-0.191***	-0.121	-0.215***	-0.001	0.105	-0.047
Rioja (La)	-0.272***	-0.218***	-0.325***	-0.092	-0.129	-0.043
Salamanca	-0.032	-0.052	-0.015	0.118*	0.095	0.144
S C Tenerife	-0.025	-0.019	-0.039	0.064	0.098	0.044
Segovia	-0.121*	0.022	-0.233**	-0.050	0.007	-0.107
Seville	-0.093***	-0.065	-0.107**	-0.043	-0.029	-0.046
Soria	-0.275***	-0.441***	-0.187*	-0.050	-0.458**	0.153
Tarragona	-0.253***	-0.307***	-0.224***	-0.229***	-0.397***	-0.049
Teruel	-0.102*	-0.059	-0.140*	-0.157*	-0.122	-0.202
Toledo	-0.169***	-0.227***	-0.142**	-0.022	-0.194*	0.079
Valencia	-0.172***	-0.147***	-0.197***	-0.049	-0.042	-0.060
Valladolid	-0.212***	-0.283***	-0.183***	-0.236***	-0.428***	-0.061

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Vizcaya	-0.145***	-0.088	-0.194***	-0.072	-0.058	-0.095
Zamora	-0.115***	0.019	-0.183***	-0.183**	-0.093	-0.218**
Saragossa	-0.110**	-0.109	-0.129**	-0.023	-0.053	0.015

Notes: *, **, and *** show s statistical significance at 10%, 5%, and 1% levels, respectively.

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Table A5. Cyclical sensitivity of the LFP. Extensions to the baseline model.

	Demographic Variables	Gender		SEM		SAR		Breaks in series	Quarterly data	
		Female	Male	5-nn	Distance	5-nn	Distance		Short term	Long term
Alava	0.016	-0.038	-0.249***	-0.011	0.069	-0.072	-0.131	-0.016	-0.039	-0.093
Albacete	0.069*	0.072	-0.061	0.077*	0.108***	0.102	0.276	0.087**	0.032	0.086
Alicante	0.010	-0.089	-0.035	-0.029	0.030	-0.098	-0.177	-0.017	-0.037	-0.094
Almeria	-0.028	0.049	-0.124***	-0.080*	-0.028	-0.218**	-0.453**	-0.062	0.050	0.127
Asturias	0.089	0.051	-0.041	0.057	0.146***	0.015	0.214	0.106*	0.071	0.191
Avila	0.041	0.117*	0.026	0.106**	0.176***	0.168*	0.458**	0.113**	-0.028	-0.070
Badajoz	0.007	0.097	0.015	0.095**	0.133***	0.045	0.222	0.082*	0.012	0.028
Balearic Islands	0.042	-0.022	-0.111*	-0.018	0.061	0.059	0.029	0.020	0.046	0.131
Barcelona	0.010	0.016	-0.106**	-0.002	0.069*	0.036	0.136	0.020	0.042	0.125
Burgos	-0.038	-0.040	-0.096	-0.043	0.052	-0.159	-0.233	-0.007	-0.053	-0.122
Caceres	0.087*	0.184***	0.069	0.139***	0.216***	0.211**	0.681***	0.198***	0.106	0.299
Cadiz	0.110***	0.152***	-0.067	0.149***	0.183***	0.164**	0.540***	0.140***	0.021	0.055
Cantabria	-0.056	-0.080	-0.181**	-0.096	0.004	-0.254**	-0.454*	-0.042	0.018	0.045
Castellon de la Plana	-0.076	-0.044	-0.159***	-0.099*	-0.048	-0.232**	-0.509**	-0.089*	-0.044	-0.089
Ciudad Real	-0.023	-0.094	-0.039	0.191***	0.294***	0.259*	0.856	0.031	0.046	0.083
Cordoba	0.026	0.137**	-0.076*	0.085**	0.128***	0.024	0.231	0.082*	0.066	0.138
Corunna (A)	0.200***	0.055	0.014	0.191***	0.111**	-0.018	0.064	0.243***	0.040	0.161
Cuenca	-0.068	0.006	-0.090	0.109*	0.138**	0.094	0.233	0.081	0.023	0.048
Girona	-0.137**	-0.211**	-0.233***	-0.215***	-0.109*	-0.425***	-0.899***	-0.164**	0.000	0.000
Granada	0.022	0.082	-0.098**	0.066*	0.113***	0.054	0.210	0.067*	0.030	0.095
Guadalajara	-0.080	-0.122*	-0.100	-0.108*	-0.015	-0.275**	-0.497**	-0.082	0.046	0.118
Guipuzcoa	-0.023	-0.108	-0.111	-0.078	0.022	-0.180	-0.323	-0.058	0.031	0.082
Huelva	0.132***	0.192***	0.044	0.140***	0.169***	0.157*	0.479***	0.137***	0.084	0.170
Huesca	0.010	0.004	-0.069	0.002	0.128*	0.012	0.176	0.030	-0.011	-0.021

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Jaen	0.022	0.231***	-0.024	0.112***	0.144***	0.128	0.388**	0.102***	-0.002	-0.005
Leon	0.012	0.063	-0.044	0.104	0.205***	0.072	0.432	0.136**	0.057	0.142
Lleida	0.031	-0.087	-0.227**	-0.060	0.079	-0.077	-0.065	-0.003	-0.088	-0.201

Table A5. (continuation)

	Demographic Variables	Gender		SEM		SAR		Breaks in series	Quarterly data	
		Male	Female	5-nn	Distance	5-nn	Distance		Short term	Long term
Lugo	0.243***	0.234**	0.007	0.362***	0.449***	0.517***	1.477***	0.369***	0.043	0.139
Madrid	-0.018	-0.109	-0.171***	-0.070	0.025	-0.224**	-0.338	-0.058	-0.016	-0.028
Malaga	0.088**	0.188***	-0.054	0.095**	0.121***	0.061	0.263	0.087**	0.011	0.028
Murcia	0.007	-0.016	-0.135***	-0.028	0.034	-0.116	-0.187	-0.018	0.021	0.049
Navarre	-0.064	-0.139	-0.117	-0.078	0.029	-0.196	-0.324	-0.066	-0.029	-0.055
Orense	-0.027	0.000	-0.163**	0.022	0.073	-0.092	-0.143	0.029	0.000	-0.001
Palencia	0.043	-0.033	0.033	0.121**	0.198***	0.228**	0.573**	0.126**	0.076	0.224
Palmas (Las)	-0.016	0.01	-0.172***	-0.057	-0.032	-0.223**	-0.437**	-0.068	0.011	0.027
Pontevedra	0.046	-0.002	-0.102	0.007	0.113**	-0.114	-0.087	0.054	0.056	0.185
Rioja (La)	-0.072	-0.080	-0.107	-0.070	-0.002	-0.185	-0.422	-0.080	0.003	0.007
Salamanca	0.073	0.085	0.008	0.148**	0.239***	0.247**	0.661**	0.191***	0.108	0.208
Segovia	-0.036	0.087	-0.052	0.007	0.131**	0.003	0.120	0.041	0.009	0.019
Seville	0.011	0.027	-0.101	0.034	0.065*	-0.132	-0.127	0.010	0.028	0.078
Soria	-0.141	0.070	-0.128***	-0.021	0.120	-0.063	-0.040	0.013	-0.026	-0.067
Tarragona	-0.105*	0.072	-0.224**	-0.158***	-0.076	-0.376***	-0.732***	-0.143**	-0.097	-0.169
S C Tenerife	0.127**	-0.200**	-0.194***	0.096*	0.133***	0.098	0.378*	0.095*	0.009	0.023

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Teruel	-0.067	-0.084	-0.159*	0.014	0.089	-0.054	-0.057	0.003	-0.081	-0.179
Toledo	-0.002	0.052	-0.153***	0.024	0.100**	-0.068	-0.015	0.036	-0.014	-0.038
Valencia	-0.013	-0.010	-0.192***	0.002	0.039	-0.087	-0.124	-0.024	-0.008	-0.021
Valladolid	-0.108*	-0.156**	-0.169**	-0.141**	-0.038	-0.388***	-0.736***	-0.109*	-0.056	-0.162
Vizcaya	-0.007	-0.082	-0.080	-0.017	0.090	-0.049	0.021	0.012	-0.031	-0.078
Zamora	-0.194***	0.021	-0.280***	-0.128**	-0.016	-0.341***	-0.603**	-0.053	0.038	0.087
Saragossa	0.017	-0.026	-0.101*	0.007	0.080	-0.020	0.056	0.013	0.023	0.062
λ				0.559***	0.826***					
ρ						0.518***	0.795***			

*, **, and *** show s statistical significance at 10%, 5%, and 1% levels, respectively.
The cyclical sensitivity in the SAR model is the sum of the direct and the indirect effect.
In the last two columns the level of significance is not included because the results are obtained by using expressions (24) and (25)

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Figure A1. Set of alternatives for the worker

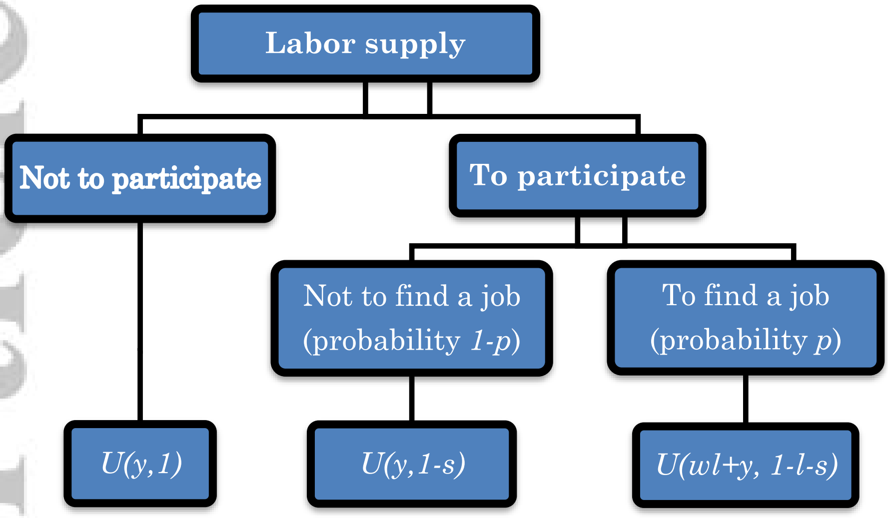

Figure A2. Scatterplot diagrams of the relationship between the cyclical sensitivities obtained by the HP method (λ=400), HP method (λ=100) and the QT procedure

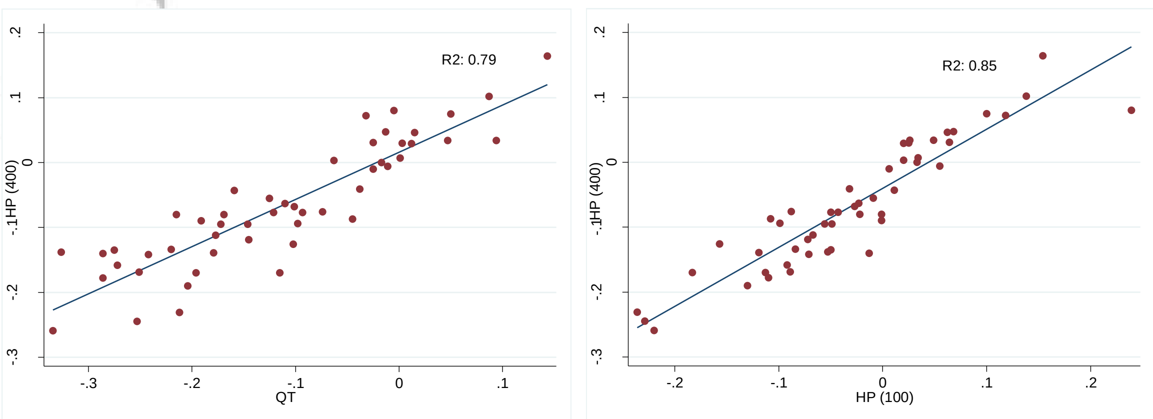

Figure A3: Local spatial dependence test (1977–2015) (HP λ=400)

5 nearest neighbor's weight matrix

Inverse distance matrix (α=1)

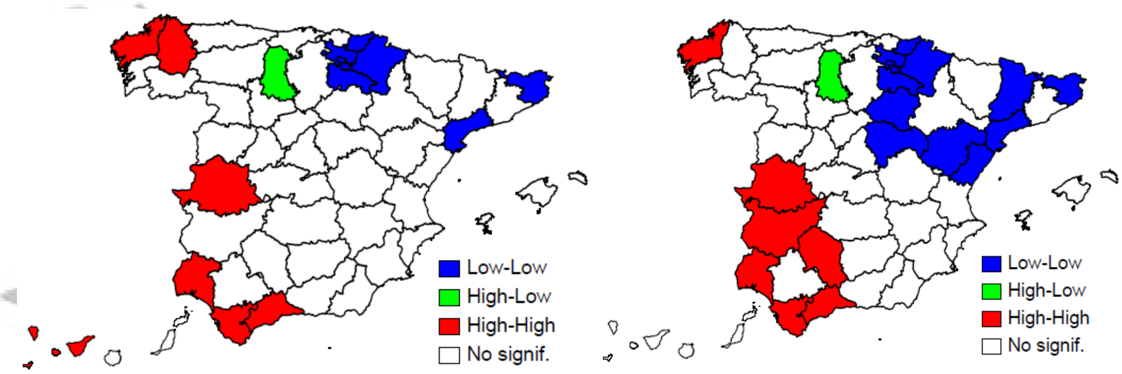

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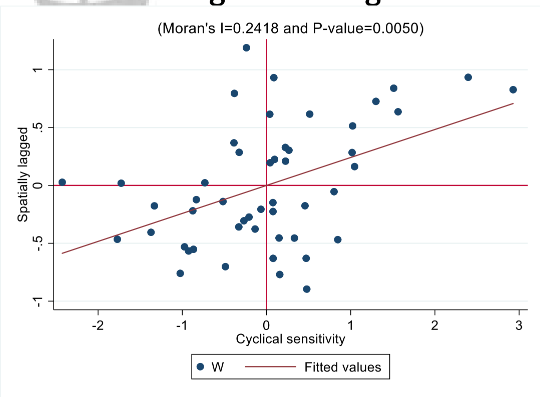
Figure A4. Global Scatterplot diagrams of Moran’s I: Population variables (1977–2015) (HP λ=400)

5 nearest neighbor’s weight matrix



Inverse distance matrix (α=1)

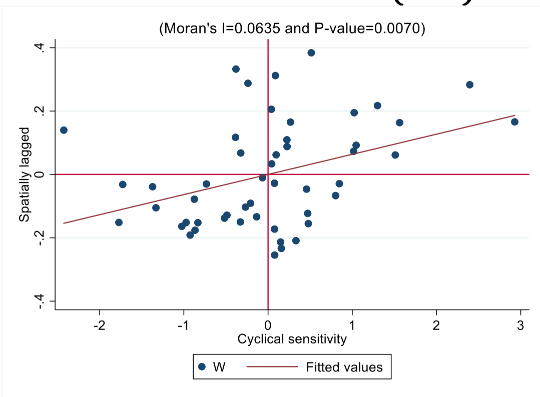
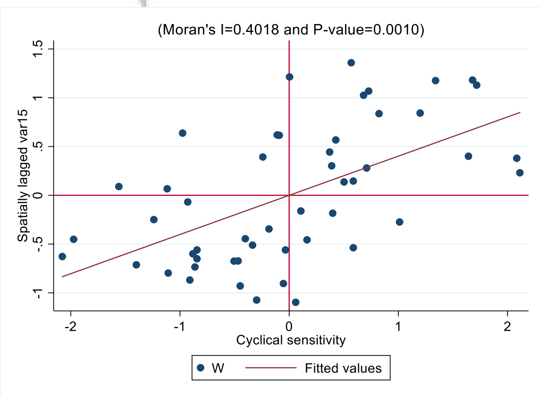


Figure A5. Global Scatterplot diagrams of Moran’s I: Females (1977–2015) (HP λ=400)

5 nearest neighbor’s weight matrix



Inverse distance matrix (α=1)

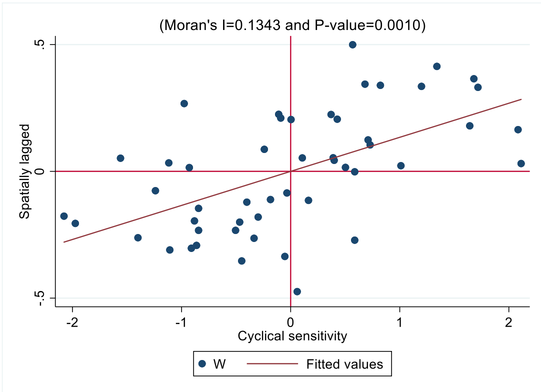
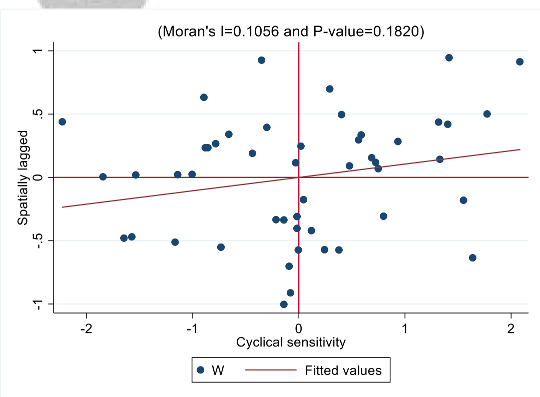


Figure A6. Global Scatterplot diagrams of Moran’s I: Males (1977–2015) (HP λ=400)

5 nearest neighbor’s weight matrix



Inverse distance matrix (α=1)

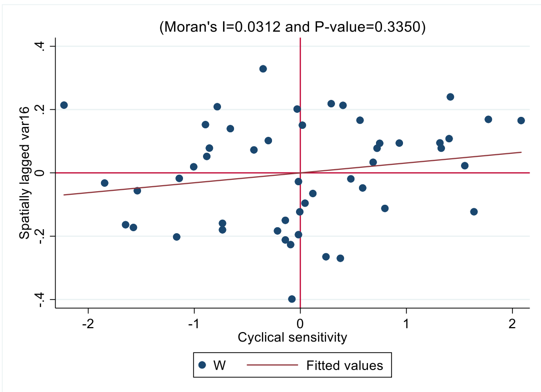


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Figure A7. Global Scatterplot diagrams of Moran's I: Labor reforms and breaks in series (1977–2015) (HP λ=400)

5 nearest neighbor's weight matrix | Inverse distance matrix (α=1)

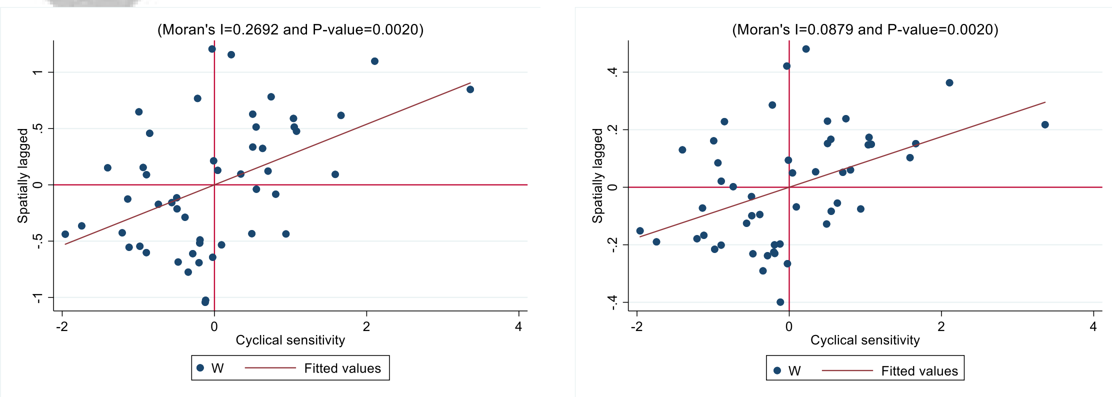

Figure A8. Global Scatterplot diagrams of Moran's I: Short term elasticity (1977–2015 quarterly) (HP λ=400)

5 nearest neighbor's weight matrix | Inverse distance matrix (α=1)

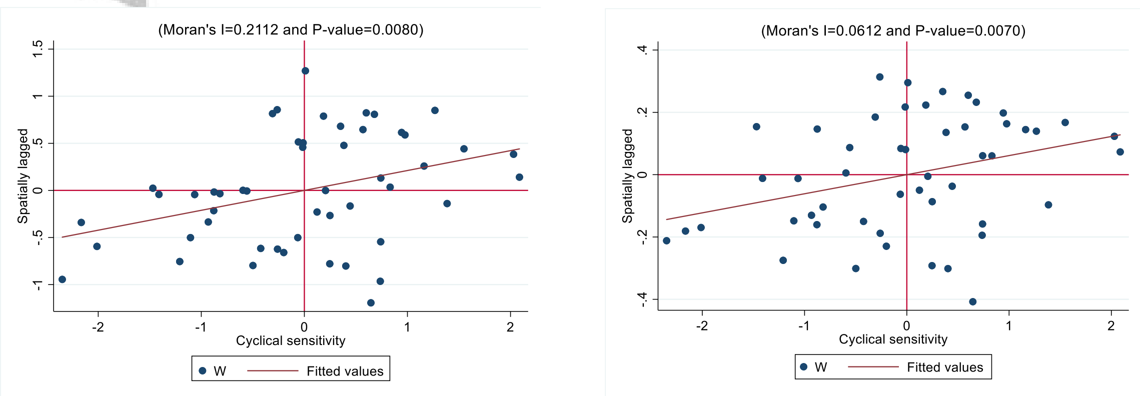

Figure A9. Global Scatterplot diagrams of Moran's I: Long term elasticity (1977–2015 quarterly) (HP λ=400)

5 nearest neighbor's weight matrix | Inverse distance matrix (α=1)

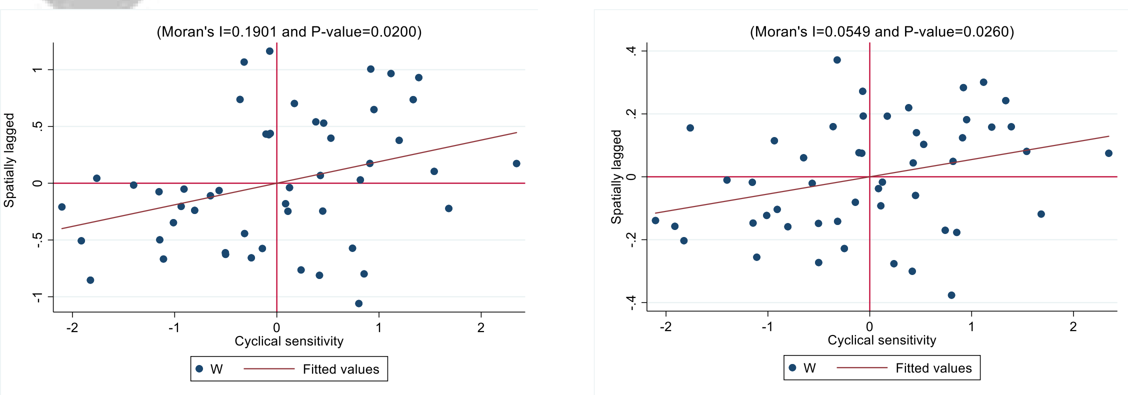

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Figure 1. Cyclical PR sensitivity of an area as a function of the cyclical PR sensitivity of neighboring areas

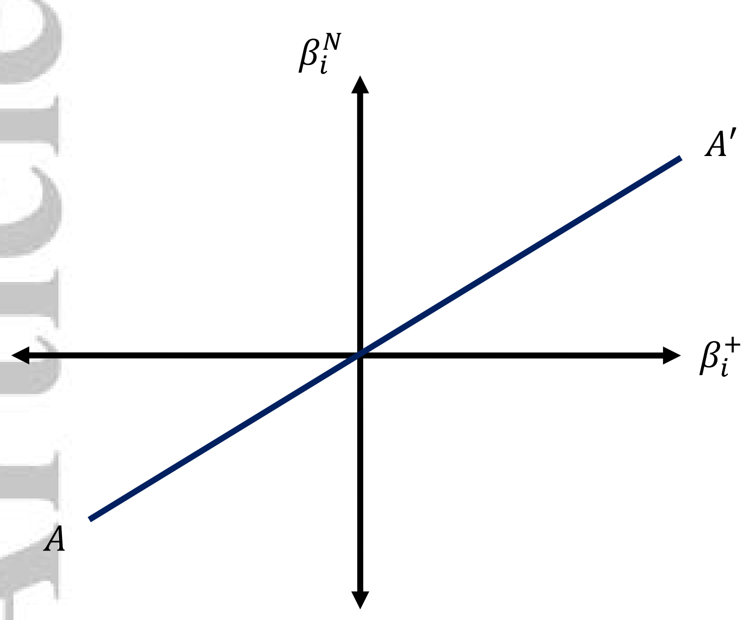

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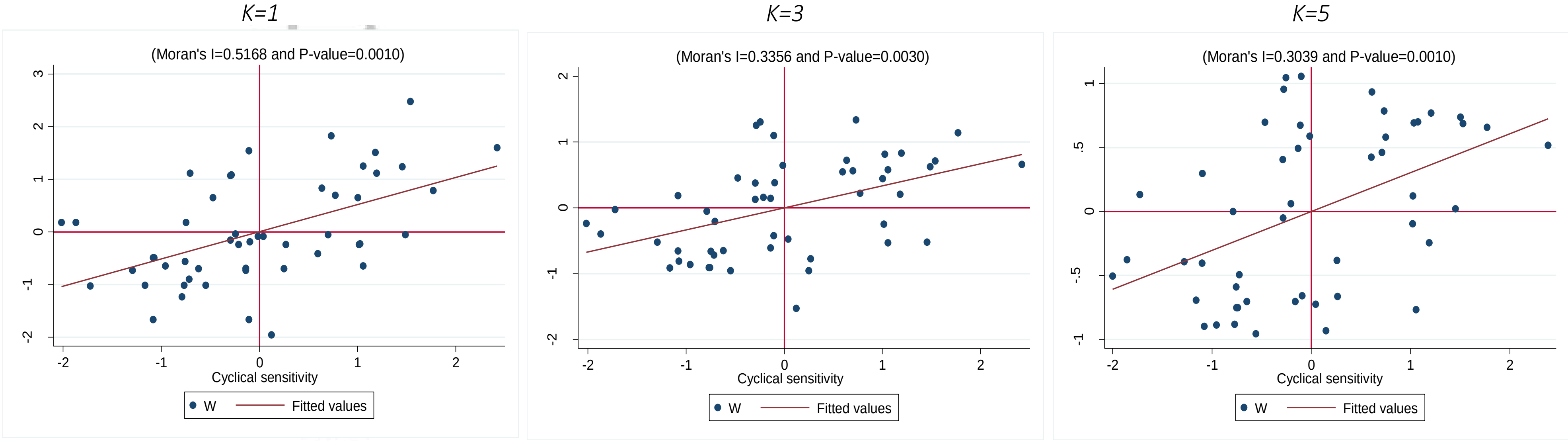
Figure 2. Global Scatterplot diagrams of Moran's I (HP λ=400) (1977–2015)



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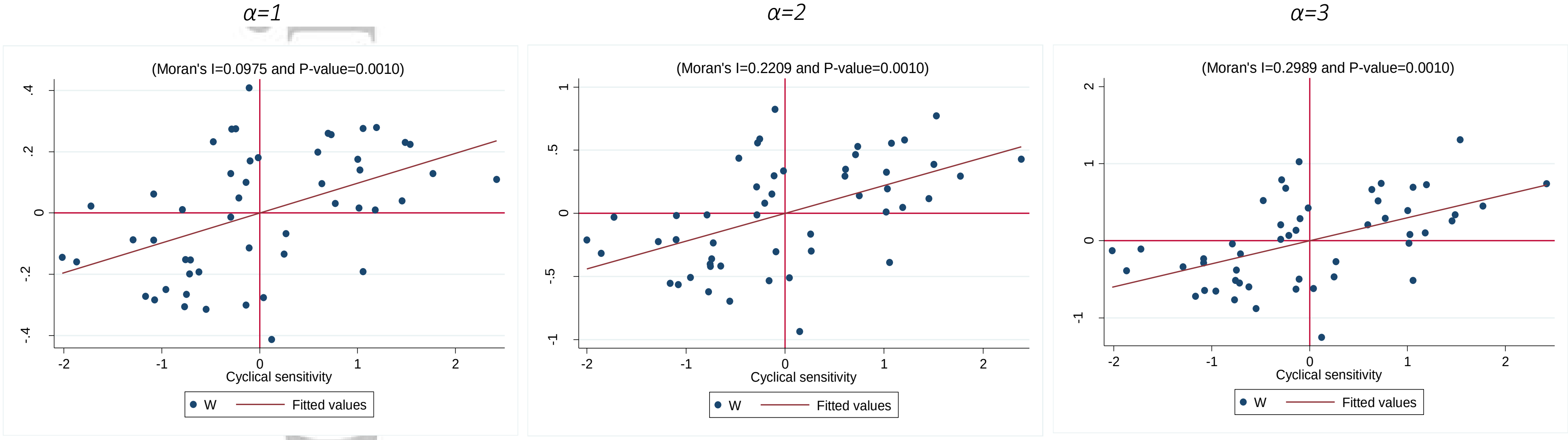

Figure 3. Global Scatterplot diagrams of Moran´s I (HP=400) (1977-2015)

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Figure 4. Evolution of the Global Spatial Dependence of the Knn matrixes (1977–2015) (HP λ=400)

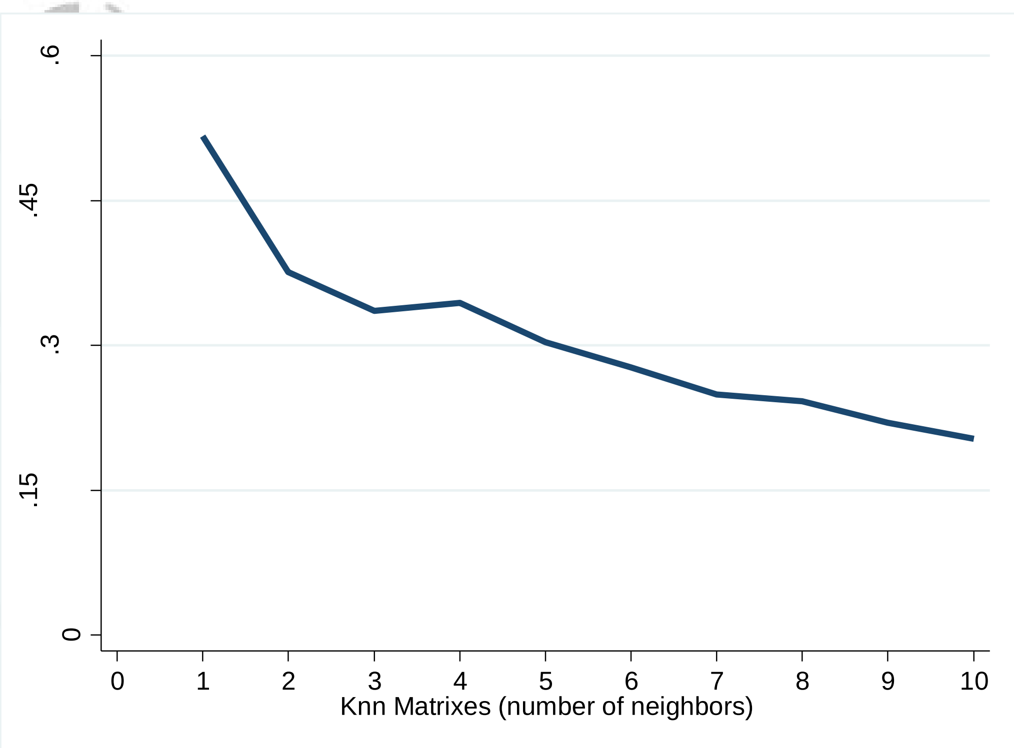
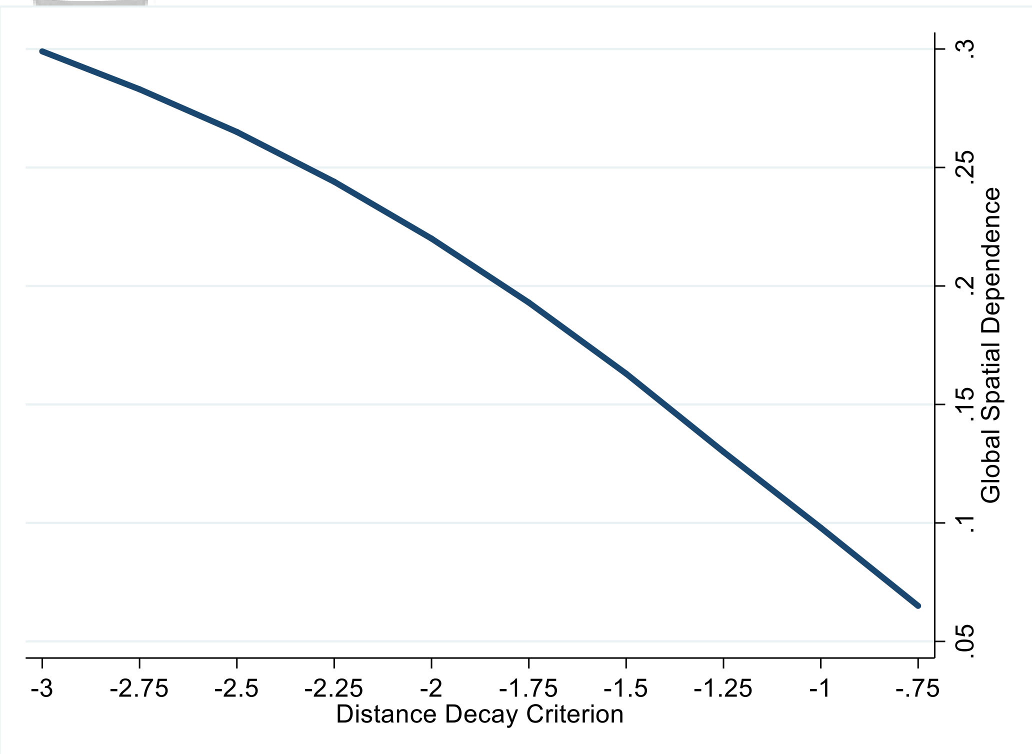


Figure 5. Evolution of the Global Spatial Dependence of the Inverse Distance matrixes (1977–2015) (HP λ=400)



Notes: Distance decay criterion is equal to the $-\alpha$ parameter of the equation that determines the spatial weights of the inverse distance matrix ($d_{ij}^{-\alpha}$).

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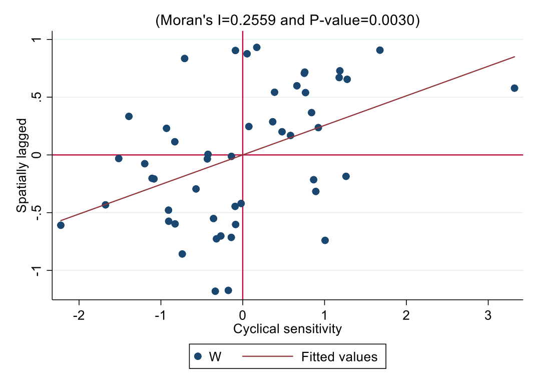
Figure 6. Global Scatterplot diagrams of Moran's I: SEM (1977–2015) (HP λ=400)

5 nearest neighbor's weight matrix



Inverse distance matrix (α=1)

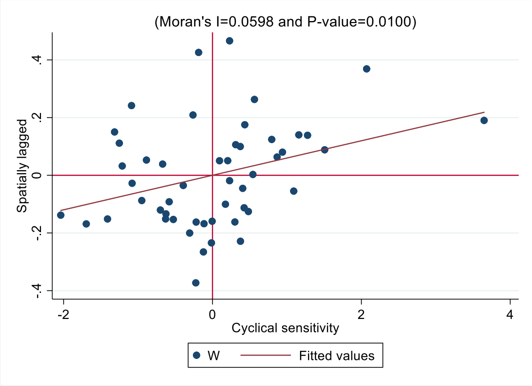
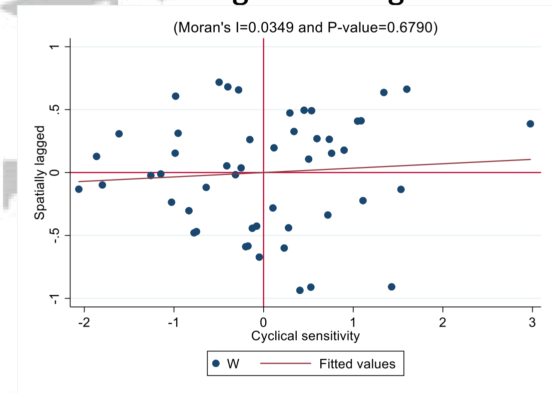


Figure 7. Global Scatterplot diagrams of Moran's I: SAR (1977–2015) (HP λ=400)

5 nearest neighbor's weight matrix



Inverse distance matrix (α=1)

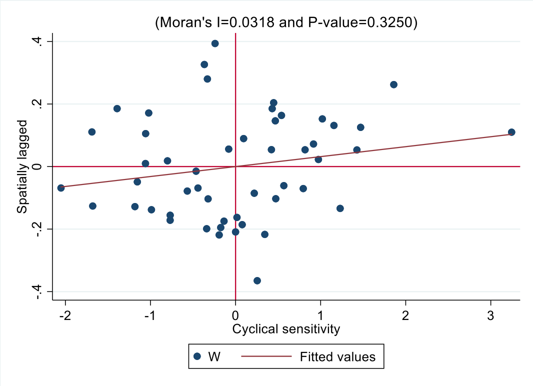


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Table 1. LFPR and spatial effects in the regional labor markets

Study	Regions	Population	Period	Method
Elhorst (2001)	France, Germany, United Kingdom (NUTS-2 and NUTS-1)	Total	1983-1993	Various (10 spatial panel data models)
Möller and Aldashev (2006)	Germany (NUTS-3)	Male, female	1998	SAR, SEM
Elhorst and Zeilstra (2007)	European Union (NUTS-1 and -2)	Male, female	1983–1997 (annual)	SEM
Elhorst (2008)	European Union (NUTS-2)	Total, male, female	1983–1997 (annual)	SEM (MESS)
Cochrane and Poot (2008)	New Zealand (LMAs)	Total	1991–2006; (quinquennial)	SAR, SEM
Falk and Leoni (2010)	Austria (districts)	Female	2001	SEM
Liu and Noback (2011)	Netherlands (municipalities)	Female	2002	SEM
Fogli and Veldkamp (2011)	EEUU (counties)	Female	1940–2000; (decennial)	TSR
Halleck Vega and Elhorst (2014)	European Union (NUTS-2)	Total	1986-2010	DSDM
Halleck Vega and Elhorst (2017)	European Union (NUTS-2)	Total, male, female	1986-2010 (annual)	TSR
Kawabata and Abe (2018)	Tokyo metropolitan area (municipalities	Female	2010	SDM,SLX

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Notes: NUTS corresponds to Nomenclature of Territorial Units for Statistics. LMAs refers to Labor Market Areas. SAR, spatial autoregressive model; SEM, spatial error model; MESS, matrix exponential spatial specification; SDM, spatial Durbin model; DSDM, dynamic spatial Durbin model; SLX, spatial lag model and TSR, time–space recursive model.
Source: Halleck Vega and Elhorst (2017) and own elaboration.

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Table 2. Cyclical sensitivity of the LFP (HP λ=400)

	1977–2015	1977–1996	1997–2015
Alava	-0.140*	-0.320***	-0.006
Albacete	0.030	-0.031	0.040
Alicante	-0.087	-0.223**	-0.007
Almeria	-0.112**	-0.557***	-0.039
Asturias	-0.006	0.001	0.009
Avila	0.046	0.185**	0.076
Badajoz	0.003	-0.207***	0.106
Balearic Islands	-0.043	-0.245**	0.038
Barcelona	-0.055	-0.052	-0.062
Burgos	-0.134*	-0.152	-0.109
Caceres	0.102**	-0.040	0.159***
Cadiz	0.047	0.012	0.050
Cantabria	-0.170**	-0.179	-0.187**
Castellon de la Plana	-0.139**	-0.275**	-0.090
Ciudad Real	-0.068	-0.105	-0.033
Cordoba	0.000	-0.173**	0.076
Corunna (A)	0.080	0.633***	-0.105
Cuenca	-0.041	-0.155	0.010
Girona	-0.259***	-0.512***	-0.142
Granada	-0.010	-0.218***	0.057
Guadalajara	-0.190***	-0.265***	-0.085
Guipuzcoa	-0.169**	-0.105	-0.293**
Huelva	0.075*	-0.112*	0.189***
Huesca	-0.080	0.002	-0.140
Jaen	0.029	-0.176**	0.130**
Leon	0.007	-0.342*	0.055
Lleida	-0.138	0.335**	-0.170
Lugo	0.164*	0.508**	0.109
Madrid	-0.142**	-0.063	-0.196**
Malaga	0.034	0.020	0.043
Murcia	-0.095*	-0.418***	-0.032
Navarre	-0.178**	-0.141	-0.194
Orense	-0.076	-0.707***	0.033
Palencia	0.034	-0.113	0.121
Palmas (Las)	-0.094*	-0.208**	-0.013
Pontevedra	-0.090	0.007	-0.115
Rioja (La)	-0.158**	-0.185**	-0.134
Salamanca	0.072	0.053	0.111
S C Tenerife	0.031	0.010	0.010
Segovia	-0.077	0.053	-0.140
Seville	-0.077*	-0.051	-0.074
Soria	-0.135	-0.526***	0.066
Tarragona	-0.245***	-0.378***	-0.116
Teruel	-0.126	-0.268*	-0.151

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Table 2. (continuation)

	1977–2015	1977–1996	1997–2015
Toledo	-0.080	-0.131	0.005
Valencia	-0.095**	-0.115*	-0.116
Valladolid	-0.231***	-0.400***	-0.117
Vizcaya	-0.119*	-0.081	-0.177
Zamora	-0.170**	-0.163	-0.213**
Saragossa	-0.063	-0.139*	-0.038

Notes: *, **, and *** shows statistical significance at 10%, 5%, and 1% levels, respectively.

Table 3. Global spatial dependence analysis (HP λ=400)

	1977–2015	1977–1996	1997–2015
Knn=1	0.517***	0.385**	0.398**
Knn=2	0.376***	0.196*	0.306***
Knn=3	0.336***	0.112	0.297***
Knn=4	0.344***	0.059	0.287***
Knn=5	0.303***	0.002	0.255***
Knn=6	0.277***	-0.015	0.259***
Knn=7	0.249***	0.003	0.218***
Knn=8	0.242***	0.003	0.228***
Knn=9	0.220***	-0.028	0.214***
Knn=10	0.203***	-0.048	0.193***
	1977–2015	**1977–1996**	**1997–2015**
ID (α=3)	0.299***	0.166**	0.238***
ID (α=2.75)	0.283***	0.144**	0.229***
ID (α=2.50)	0.265***	0.121**	0.219***
ID (α=2.25)	0.244***	0.098**	0.206***
ID (α=2)	0.220***	0.075*	0.190***
ID (α=1.75)	0.193***	0.053*	0.170***
ID (α=1.50)	0.163***	0.033	0.147***
ID (α=1.25)	0.130***	0.016	0.121***
ID (α=1)	0.098***	0.003	0.093***
ID (α=0.75)	0.065***	-0.007	0.064***

Notes: The values in the table refer to the Global Moran's I. The null hypothesis refers to the absence of spatial dependence. *, **, and *** show statistical significance at 10%, 5%, and 1% levels, respectively.

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