PAPER

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

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Abstract: *The relationship between the labor force participation and the business cycle has become a topic in the economic literature. However, few studies have considered whether the cyclical sensitivity of the labor force participation is influenced by "social effects". In this paper, we construct a theoretical model to develop the "Added Worker Effect" and the "Discouraged Worker Effect", and we integrate the "social effects", coining a new concept, the Bandwagon Worker Effect (BWE). To estimate the cyclical sensitivity of the labor force participation, we employ a panel dataset of fifty Spanish provinces for the period 1977–2015. Finally, we use spatial econometrics techniques to test the existence of the BWE in the local labor markets in Spain. Our results reveal that there exists a positive spatial dependence in the cyclical sensitivity of the labor force participation that decreases as we fix a laxer neighborhood criterion, which verifies the existence of the BWE. From the perspective of economic policy, our work confirms*

that "social effects" play a key role at the time of determining the economic dynamics of the territories.

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

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

1. Introduction

The aim of this paper is to analyze how the relationship between the business cycle and the labor force participation (LFP, hereafter) may be influenced by "social effects". The so-called "Bandwagon Effect" (BE, hereafter) is now an important element to better understand the demand for goods and services (Leibenstein, 1950). As the labor supply is, in the end, a demand for leisure, we deem that the BE might be also operating in the labor market. As a matter of fact, some studies are already exploring this possibility (Blomquist, 1993; Vendrik, 1998; Grodner and Kniesner, 2006; 2008). However, our research goes one step ahead in linking this social effect to the cyclical properties of LFP and in defining a relatively new hypothesis, the "Bandwagon Worker Effect" (BWE, hereafter). As far as we know, this is the first time that this hypothesis has been presented and discussed as such.

The relationship between the business cycle and LFP has produced much academic work. The reason for this might be its great importance in understanding the functioning of the macroeconomic labor market (e.g., an adequate count of the "actual" unemployed workers in the economy, the magnitude of the "hidden unemployment", etc.). This body of research has given rise to two key concepts: the "Added Worker Effect" (AWE, hereafter) and the "Discouraged Worker Effect" (DWE, hereafter), which will be explained in considerable detail later. Here, we develop a theoretical framework, in which the BWE interacts with the AWE and DWE, and we test empirically whether the BWE is a significant factor, when considered together with the AWE and the DWE, to better understand cyclical movements in labor supply.

To do this, first we elaborate a microeconomic decision model, in which the AWE is conceptualized as an income effect and the DWE as an effect depending on the expectations of finding a job. These are the theoretical channels through which the original ideas of Woytinsky

(1940) and Humphrey (1940) about AWE, and Long (1953) and Mincer (1962) over DWE should operate. Then, we discuss the aggregation process, since, in the end, we are interested in a macroeconomic perspective. The next step is incorporating the BWE within the previous theoretical framework, under the assumption that the BWE is a social effect. Finally, we test empirically the relevance of the BWE in our data by means of spatial econometrics' techniques.

As for the contribution of this piece of research to the existing literature, to the best of our knowledge, the notion of BWE had not been analyzed in a systematic way so far. It is true that some papers have addressed the idea 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); however, none of them have studied explicitly the effect of that "social influence" on the cyclical sensitivity of aggregate labor supply. Put differently, although the BE had already been tackled in relation to the labor market functioning, the idea of BWE as such, and its implications for the cyclical behavior of aggregate labor supply, is still an emerging research question. Hence, we deem that the theoretical conceptualization and modelling of the BWE is a first contribution to the state of the art.

Another feature that adds to the originality of this paper is the manner in which we test empirically the theoretical predictions of our model. We make use of conventional spatial econometrics techniques to do that. Moreover, the empirical test is derived straightforwardly from the theoretical framework. It could be stated that several papers analyzing some spatial aspects of the aggregate labor markets have been published recently (e.g., Overman and Puga, 2002; Cracolici et al., 2007; Halleck-Vega and Elhorst, 2014; 2017). However, it has to be pointed out that, in this piece of research, the spatial analysis is not an end in itself but just a means to check whether the notion of the BWE is relevant. More precisely, we assume here that geographical neighborhood is a tool to capture the degree and the intensity of the "social effects", as will be explained in greater detail later. This empirical strategy has been employed before, although not coming directly from a theoretical model, as is done in the present paper.[1] Thus, this approach adds extra value to the article.

The results obtained show a positive and significant global spatial dependence in the cyclical sensitivity of the LFP in the Spanish provinces (NUTS-3 regions).[2] 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. This result is robust to two different neighborhood criteria and two different trend-cycle decompositions of time series. Moreover, we also find that, as the neighborhood definition becomes laxer, the strength of the "social effect" diminishes. This outcome is consistent with the overall theoretical framework developed here, which might be also considered as either an additional sensitivity analysis or an extra robustness check, and, thus, gives the paper more credibility.

Other relevant aspects can be obtained from this work, most of them having to do with economic policy implications. Thus, policy makers should take into account, when designing their economic policy measures, that there are geographical social effects affecting labor supply that might condition such measures. Particularly, the economic policy ought to be implemented on a geographical basis. Spatial areas, instead of single spatial units, should be the economic policy target when devising policy actions thought to improve problems related to the cyclical pattern in labor supply (e.g., hidden unemployment in recessions).

[1] See Martín-Román et al. (2015) for an application of this type of econometric technique to analyze the presence of peer effects in the judicial decisions in Spain.
[2] 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.

The remainder of the work is organized as follows. Section 2 discusses the state of the art and the empirical strategy. Section 3 offers a review of the literature related to the topic in hand. Section 4 develops the theoretical model. Section 5 presents the methodology and the database used both to study the relationship between the local labor participation rates (PRs, hereafter) and the business cycle and to test the BWE. Section 6 describes and explains the results obtained in the cyclical sensitivity analysis and in the spatial dependence analysis. Section 7 includes some extensions to the empirical analysis and sensitivity checks. Section 8 offers some economic policy implications of our results. Finally, section 9 sums up the most relevant conclusions.

2. State of the art and empirical strategy

To the best of our knowledge, the study of the influence of social effects on the cyclical behavior of LFP has not been done in a systematic way. We should point out, however, that some research works have addressed the relationship between labor force and social effects in general terms, and they will be reviewed in the next section. Notwithstanding, as stated above, the aim of the paper is not so much to carry out an additional test on this relationship as to define a relative new notion that we name BWE. The BWE could be understood as the application of the BE to the analysis of the cyclical behavior of the LFP. Hence, despite the fact that the BE has received some attention in the study of labor markets, since labor supply is at the same time a demand for leisure, we deem that the hypothesis of BWE is somewhat novel.

In order to define, formalize and test the BWE, we proceed in several steps. As will be shown later on in the paper, first we build a microeconomic model to formalize the AWE and DWE. Secondly, we discuss the aggregation process as this paper in the end adopts a macroeconomic approach. Then, in our aggregate LFP formal framework the BWE notion is inserted and, importantly, a theoretically derived function is obtained to test such an effect.

Moreover, it is proved that that theoretical function corresponds to the Moran's I curve, so the empirical test is straightforward by just making use of standard spatial econometrics' techniques. Finally, some alternative spatial econometric models are estimated to check the robustness and sensitivity of the results.

The main hypothesis 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, we develop a conceptual framework, in which the individuals emulate to some degree their neighbors' behavior as to their labor supply decisions. This microeconomic individual behavior has to be scaled up to macroeconomic size since this paper makes use of aggregate data. In this vein, our theoretical framework, firstly, describes the required aggregation process and, secondly, bridges the gap between the notion of "social effect" and the spatial analysis that will be used to test whether such an effect is relevant.

Hence, what we expect is that the LFP rate of a spatial unit is influenced by the PRs in neighboring areas. Even more precisely, the above-mentioned "social effect" may also be interpreted as a positive spatial correlation among the spatial units considered. Thus, the previous discussion implies that the PR of a spatial unit surrounded by high-level PR spatial units would be higher than otherwise, and vice versa. As will be formally proved later, this positive spatial correlation between the levels of PRs can be translated into a positive spatial correlation between the cyclical sensitivity of those PRs. This is what, in the end, allows us to make use of a well-known spatial analysis tool, the Moran's I scatterplot, to test the theory in a straightforward manner. It is also worth mentioning that we check not only the sign of the relationship but also its intensity. We hypothesize that the higher the level of closeness or neighborhood, the stronger the "social effect". To validate this derivative hypothesis, we define several neighborhood spatial matrixes, ordering them from most to least spatial closeness, and verify whether the spatial pattern we expect is fulfilled.

We use Spanish data, and from our standpoint this choice has an important advantage: the amplitude of the Spanish business cycle is larger than that of most of the developed countries, where it is possible to find time series long enough and with an appropriate spatial disaggregation to make feasible a study like this one. In this vein, Ball et al. (2017), Bande and Martín-Román (2018) and Porras-Arena and Martín-Román (2019) provide some empirical evidence of the large size of the Spanish business cycle, particularly with regard to the labor market outcomes. On the other hand, Spain is made up of 50 NUTS-3 spatial units, which allow us to apply spatial econometric techniques with a high degree of reliability and accuracy.

3. Literature review

From the previous discussion, it follows that several strands of literature are relevant to our inquiry. To start with, the research works on the LFP pattern over the business cycle constitute the conceptual basis on which we can build our approach. The spatial analysis is also at the core of this research. This is so because our theoretical framework predicts a spatial relationship affecting the LFP reaction to the business cycle and because such a relationship is then tested by means of spatial econometrics' techniques. This entails that the literature analyzing spatial labor markets functioning is also of interest for the purposes of this paper. Finally, the last strand of literature involved here is that which examines the influence of social effects on the labor market outcomes, particularly those research works making use of spatial analysis to determine such social effects influence.

The relationship between the LFP and the business cycle has been an active research topic for decades. Probably, this is so 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. As mentioned above, the two key concepts in the relationship between the business cycle and the LFP are the AWE and the DWE hypotheses. The two seminal works related to the AWE are Woytinsky (1940) and Humphrey (1940). On the other hand, the origin of the DWE can be found in Long (1953) and Mincer (1962).

According to the conventional view of the AWE (Woytinsky, 1940), some breadwinners lose their jobs during an economic downturn. As a consequence of this, their spouses would experience a reduction in their non-labor income, and this, in turn, would reduce their reservation wage, and, at an aggregate level, labor force would rise. The opposite would be true in an economic boom. Hence, this effect establishes that the LFP maintains countercyclical behavior, implying 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 falls, some workers quit active job searches (i.e., they become inactive) and that the opposite occurs when the likelihood of finding a job rises. The rationale behind this is that, as the expectations of finding a job worsen, the transaction costs linked to the search process could exceed the benefits expected from it, since these expected benefits diminish. To sum up, through this effect, it can be stated that the unemployed workers leave the labor force during the recessive phases of the business cycle and vice versa. Put differently, the LFP exhibits a pro-cyclical pattern entailing an underestimation of the unemployment rate in booming periods and an overestimation of it during downturns and recessions.

As these two hypotheses predict opposite patterns for LFP changes throughout the business cycle, determining which one prevails over the other is an empirical question. The observed evidence about these two effects is mixed, with some studies pointing to a prevalence of AWE over DWE and others stating that DWE is stronger than AWE, depending on various factors of the labor market analyzed (geographical location, gender, etc.). For instance, in Wachter (1972, 1974) and Tano, (1993) neither of these effects are found to be predominant over the other. This fact might be interpreted as an example of a situation in which both effects offset each other.

There are also some studies in which the AWE dominates over the DWE. For example, the AWE dominates in Maloney (1987), where 1.585 couples are analyzed in the case of the USA. Emerson (2011) also finds this effect being prevalent during the period 1948–2010. In the work of Del Boca et al. (2000) the AWE is also found (in net terms) in Italian households, where female participation in the labor market is not seen as "social stigma". Ghignoni and Verashchagina (2016) also identify the same effect for Italy. Parker and Skoufias (2004) detect empirical evidence of a prevailing AWE in Mexico during the periods 1994–1995 and 1995–1998. Other research that offers empirical evidence of importance of the AWE is the work of Gałecka-Burdziak and Pater (2016), for Poland. In the Spanish case, this effect is found dominant in Prieto-Rodríguez and Rodríguez-Gutiérrez (2000, 2003), and partially in Congregado et al. (2011).

As regards the research works finding a prevailing DWE, the pioneering work by Long (1958) shows that this effect predominates in the USA during the "severe recessive phases of the business cycle". Another seminal paper, Clark and Summers (1981) obtain analogous results, when focusing on the behavior of different demographic groups. Similarly, Leppel and Clain (1995) detect the prevalence of this effect in focusing on the gender of the individuals. Benati (2001) shows empirical evidence supporting a stronger DWE from an aggregate point of view. In Darby et al. (2001), the DWE is predominant for the case of women between forty-five and fifty-

four years old in Japan, France, and the USA. In the same vein, empirical evidence of a noticeable DWE, in net terms, is 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.

As can easily be imagined from the previous discussion, spatial analysis of the regional labor markets will be a key element in this research. In this way, it could be stated that the growing interest of economists in knowing the economic dynamics from a territorial perspective, as well as the gradual development of spatial econometric techniques, has resulted in a great amount of academic research in recent decades. Some seminal works in this area are 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, there are studies analyzing the differences in the unemployment rates among territories (countries, regions, etc.) 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; Cuéllar-Martín et al. 2018). Furthermore, other studies focus on the role that space plays in the process of matching the individuals in the labor market (Haller and Heuermann, 2016).

In any case, this paper intends to go one step further in analyzing the cyclical properties of the LFP. We consider that social effects, which have been proved to exert influence on several economics outcomes, play an important 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). Briefly, this is a phenomenon whereby individual’s preferences and decisions are affected by the behavior of other individuals’ belonging to his/her social group.

In the case of economics (particularly in microeconomics), a type of social effect has been named as BE for the demand of goods and services. Such effect establishes that the behavior of an individual is not only determined by his/her personal features but it's also influenced by the actions and decisions of his/her peers (Leibenstein, 1950; Pollak, 1976; Granovetter and Soong, 1986; Van Herpen et al., 2009). As the labor supply is in the end a demand for leisure, we deem that the BE might be operating in the labor markets too.

For this reason, here we are interested in those studies applying the social effects approach so as to analyze the participants' behavior in the labor market. For example, the works by Hellerstein et al. (2011) and Hellerstein et al. (2015) highlight role of networks defined by residential neighborhoods on employment and re-employment opportunities, especially for minorities and the less skilled. These studies find empirical evidence supporting the idea that social effects, or network effects in their terminology, are really important to understand local labor market functioning. Loog (2013) also shows that social effects are important to understand certain outcomes observed in the labor market. More precisely, this author analyzes the significance of social effects in relation to the working hours by using a sample of public workers in Germany between 1993 and 2005. In the same vein, Collewet et al. (2017) point out that there is a small peer effect in the working time of a sample of Dutch male employees during 1994–2011. Similar results can be found in Weinberg et al. (2004).[3]

Even more closely related to the ultimate aim of the paper, it could be emphasized that the connection between social effects and labor supply from a microeconomic perspective has produced a number of academic works too. For instance, Blomquist (1993) elaborates a model

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

where the worker's preferences regarding labor market outcomes are interdependent with other individuals' behavior. Likewise, there are studies where the decision to participate in the labor market is influenced by either the action of the so called "social group" or the existence of a "social norm." Vendrik (1998, 2003) establish that the 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), Grodner and Kniesner (2006, 2008). Finally, Woittiez and Kapteyn (1998) and Maurin and Moschion (2009) also find relevant social effects in the labor supply of women.

Notwithstanding, it is worth stressing that our study combines the micro and macro perspectives, together with a spatial dimension. For this reason, there is an important body of research closely related to this investigation: that analyzing spatial dependence among LFPR. Table 1 summarizes this strand of literature succinctly. It has been elaborated by taking the work by Halleck Vega and Elhorst (2017) as a reference and adding some extra studies to these authors' compilation.

[INSERT TABLE 1 HERE]

First, there is a group of studies that, from a more general standpoint, offer empirical evidence on the importance of accounting for spatial effects in the labor market analysis. Here, the works by Elhorst (2001), Cochrane and Poot (2008) and Halleck Vega and Elhorst (2014, 2017) may be included.

Then, there is a second group of studies more specifically focused on the LFPR analysis from a spatial perspective. Elhorst and Zeilstra (2007) investigate the underlying factors behind the heterogeneity of the LFPRs within the European regions. In a similar vein, Elhorst (2008), making use of annual data from 154 NUTS-2 regions across ten European Union member states, concludes that LFPRs appear to be strongly correlated in time, weakly correlated in space and to parallel their national counterparts. Möller and Aldashev (2006) explicitly link the social effects conceptual framework to spatial analysis, as we do in this paper. More particularly, those authors employ spatial econometric techniques to test the existence of social effects in the LFPRs in West and East Germany.

Finally, there are a number of studies that focus their attention on the female labor market participation. Falk and Leoni (2010) provide empirical evidence on a negative spatial relationship among the female LFPRs in the Austrian districts during the year 2001. In a similar context, the work by Liu and Noback (2011) apply a SEM model to detect that the female LFPR in the Netherlands is determined by age, male unemployment rate, lagged female unemployment rate, female-dominated sectors and socio-economic status. From a more theoretical point of view, Fogli and Vedkamp (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 different groups of women in the metropolitan area of Tokyo.

4. Theoretical model

4.1. Basic theoretical setting

In this section, we construct a labor market participation model. As we are interested in the extensive margin of the labor supply, we consider a fixed working week. In this way, labor supply choices coincide with participation decisions. Some examples of this kind of model can be found in Boeri and van Ours (2013), Cahuc et al. (2014), and Martín-Román (2014). However, that model is here extended to take into account the effects of unemployment. Some important assumptions of the model are listed below:

Assumption 1. *Labor is homogenous. This implies that the wage is the same for all workers.*[4]

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 the next assumption.*

Assumption 3. *A certain amount of time is associated with labor participation. Before signing a new contract, the worker has to devote s units of time to job-searches. Here, s is considered to be a fixed and exogenous sum of time.*[5]

[4] This assumption is adopted because of the macroeconomic orientation of the paper.
[5] It is out the scope of the paper to consider s as 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 kind of literature are Tatsiramos and van Ours (2012) and Tatsiramos and van Ours (2014).

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.*[6]

Assumption 5. *The size of the working week, which we denote by $\bar{l}$, is fixed and exogenously determined.*[7]

Assumption 6. *The utility function is additive. To put it another way, 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 $U(C, H) = \Lambda(C) + \Omega(H)$. As usual, marginal utilities are supposed to be positive and decreasing.*[8]

The set of alternatives for the worker is shown in Figure 1. Inside the utility function, the levels of consumption and leisure have been replaced by the corresponding values associated with each decision. In this way, we are already taking into account the budget constraints within the choice framework. As can be seen in Figure 1, 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.

(INSERT FIGURE 1 HERE)

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

[7] As we are interested in the extensive margin of the labor supply, this assumption allows us to focus on the participation decision.

[8] This assumption is less restricting than it seems at first glance. Firstly, it is well known that 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.

According to Figure 1, an individual has two options. Each of these options is associated with a level of utility, either certain or expected: (1) not to participate and (2) to participate, which can be formalized, respectively, as:

$$U(y, 1) \tag{1}$$

$$pU\left(w\bar{l} + y, 1 - \bar{l} - s\right) + (1 - p)U(y, 1 - s) \tag{2}$$

The reservation wage for an individual (w^R) might be defined, as usual, as the value of w equating both options. It is easy to prove from expression (3) that w^R is always positive ($w^R > 0$): [9]

$$pU\left(w^R\bar{l} + y, 1 - \bar{l} - s\right) + (1 - p)U(y, 1 - s) = U(y, 1) \tag{3}$$

4.2. Aggregation process

If workers have different preferences over consumption–income and leisure–work and different non-labor incomes, they will also have different reservation wages. This diversity of reservation wages $w^R \in [0, +\infty)$ might be represented by a cumulative distribution function $\phi(\cdot)$. If the rest 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 according to (4):

$$L = N \cdot \phi(\cdot) \tag{4}$$

[9] Focusing first on leisure time we have that $1 > (1 - s) > (1 - \bar{l} - s)$. This would entail that $w^R\,\bar{l} > y$ in order to attain an equality in (3), which in turn implies that $w^R > 0$.

where L stands for the labor force, and N stands for total working age population. Therefore, the PR is simply $\phi(\cdot)$, as expressed in equation (5):

$$PR = \frac{L}{N} = \phi(\cdot) \tag{5}$$

Inasmuch as $\phi(\cdot)$ is a cumulative distribution function, by definition, that proportion is increasing in its argument, $\phi_w > 0$. Nevertheless, as we will show below, not only the non-labor income but also the likelihood of finding a job plays an important role in determining PR, because both of them do change. To incorporate this idea, let us call w_M^R the reservation wage for the median individual within the cumulative distribution. In this way, a stylized PR function could be described by means of expression (6):

$$PR = \phi(w, w_M^R) \tag{6}$$

As mentioned before, $(\partial PR/\partial w) > 0$, by definition. Furthermore, it is consistent with the concept of a reservation wage $(\partial PR/\partial w_M^R) < 0$. Finally, it is worth recalling that w_M^R is, in turn, a function of some additional arguments. In the model developed here, w_M^R will depend on y and p. In addition, we must point out that both $y(Z)$ and $p(Z)$ are regarded as functions of the business cycle (Z). We will consider that, if our measure of the business cycle (Z) increases, the state of the economy improves, whereas, when Z decreases, the economy worsens. Thus, we may rewrite expression (6) as follows[10]:

[10] 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 $\phi(\cdot)$ comes from Cahuc and Zylberberg (2004). The idea of PR function depending on the reservation wage of the median individual which, in turn, depends on the business cycle is ours.

$$PR = \phi(w, w_M^R[y(Z), p(Z)]) \tag{7}$$

Equation (7) reveals that PR depends on the business cycle through a double channel: cyclical variations in the median worker's non-labor income that will give rise to the AWE, and cyclical changes in the likelihood of finding a job that will result in the DWE.

4.3. The Added Worker Effect

As pointed out above, the AWE is driven by one spouse's non-labor income variations as a result of the other spouse changes in his/her labor market status. It is easy to demonstrate that this result fits well in our theoretical framework. We first create an implicit function $R(\cdot) = R\left(w_N^R, y, p, \bar{l}, s\right)$ from equation (3), which is defined by the following expression:

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

and then we make use of the implicit function theorem:

$$\frac{\partial w_N^R}{\partial y} = -\frac{\partial R/\partial y}{\partial R/\partial w^R} = -\frac{pU_C\left(w_N^R\bar{l} + y\right) + (1 - p)U_C(y) - U_C(y)}{p\bar{l}U_C\left(w^R\bar{l} + y\right)} > 0 \tag{8}$$

It is quite evident that a reduction of the non-labor income (as a consequence of a downturn) would decrease the reservation wage of the median worker. This, in turn, would encourage labor participation. In more formal terms (maintaining p constant), we may characterize the AWE by means of (9):

$$\left.\frac{\partial PR}{\partial Z}\right|_{\bar{p}} = \frac{\partial PR}{\partial w_M^R} \cdot \frac{\partial w_M^R}{\partial y} \cdot \frac{\partial y}{\partial Z} < 0 \tag{9}$$

since 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).

4.4. The Discouraged Worker Effect

As has been already explained, the DWE operates through changes in expectations of finding a job. Hence, the way of formalizing the DWE within the model is by means of p. Taking equation (3) and making use again of the implicit function $R(\cdot) = R\left(w_N^R, y, p, \bar{l}, s\right)$, it is straightforward to compute the effects of changes in p on w^R:

$$\frac{\partial w^R}{\partial p} = -\frac{\partial R / \partial p}{\partial R / \partial w^R} = -\frac{U\left(w^R \bar{l} + y, 1 - \bar{l} - s\right) - U(y, 1 - s)}{p \bar{l} U_C\left(w^R \bar{l} + y\right)} < 0 \tag{10}$$

The negative sign of (10) is the result of the definition given in (3). First, it is obvious that $U(y,1) > U(y, 1-s)$. Second, to achieve equality in (3) $U\left(w^R \bar{l} + y, 1 - \bar{l} - s\right) > U(y,1) > U(y, 1-s)$ must be fulfilled. In other words: when p rises (drops), w_N^R decreases (increases). It is possible to obtain a stylized mathematical version of the DWE (maintaining non-labor income constant) through expression (11):

$$\left.\frac{\partial PR}{\partial Z}\right|_{\bar{y}} = \frac{\partial PR}{\partial w_M^R} \cdot \frac{\partial w_M^R}{\partial p} \cdot \frac{\partial p}{\partial Z} > 0 \tag{11}$$

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).

4.5. The Total Effect

Once we have described the two theoretical effects separately, we put them together and analyze their effects jointly. When, for instance, the economy enters a recession, the PR would fall as a consequence of the DWE and experience an increase because of the AWE. What may be observed directly through the data is the net effect, i.e., the sign of (12):

$$\frac{\partial PR}{\partial Z} = \underbrace{\frac{\partial PR}{\partial w_M^R}}_{(-)} \left(\underbrace{\frac{\partial w_M^R}{\partial y} \cdot \frac{\partial y}{\partial Z}}_{AWE(+)} + \underbrace{\frac{\partial w_M^R}{\partial p} \cdot \frac{\partial p}{\partial Z}}_{DWE(-)} \right) = \beta^* \gtreqless 0 \tag{12}$$

4.6. The Bandwagon Worker Effect

The aim of this paper, however, is twofold: first, defining and formalizing a second-order theoretical effect: the BWE; and, second, testing such an effect through 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 rather direct way 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, in turn, also depends on the business cycle.[11] In formal terms:

[11] 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 will go into further details explaining how we measure this in practical terms.

$$PR = \phi(w, w_M^R[y(Z), p(X), PR^N(Z)]) \tag{13}$$

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 will demand 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, now, the total effect of the business cycle on labor market participation might be stated formally by expression (14), instead of by (12):

$$\frac{\partial PR}{\partial Z} = \underbrace{\frac{\partial PR}{\partial w_M^R}}_{(-)} \left(\underbrace{\frac{\partial w_M^R}{\partial y} \cdot \frac{\partial y}{\partial Z}}_{AWE(+)} + \underbrace{\frac{\partial w_M^R}{\partial p} \cdot \frac{\partial p}{\partial Z}}_{DWE(-)} + \underbrace{\frac{\partial w_M^R}{\partial PR^N} \cdot \frac{\partial PR^N}{\partial Z}}_{BWE(?)} \right) = \beta^+ \gtreqless 0 \tag{14}$$

As can be appreciated in expression (14), 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, it is not possible to affirm that β^* is either higher or lower than β^+. In fact, the BWE is found to be relevant to understanding labor market participation, since the second-order derivative calculated in expression (15) has a well-defined positive sign:

$$\frac{\partial^2 PR}{\partial Z \partial \left(\frac{\partial PR^N}{\partial Z} \right)} = \frac{\partial PR}{\partial w_M^R} \cdot \frac{\partial w_M^R}{\partial PR^N} > 0 \tag{15}$$

In words, expression (15) tells us that the PR cyclical pattern of a specific area is positively related to the cyclical pattern shown in the PRs of neighboring areas. Put another way, 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 (16) and

$$\frac{\partial \beta_i^N}{\partial \beta_i^+} > 0 \tag{16}$$

The mathematical relationship shown in (16) could be graphically depicted as line AA' in Figure 2. However, this apparently trivial diagram has a powerful and 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. Put differently, Figure 2 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 it is relevant to understanding the PR cyclical patterns. This will be done in a subsequent section.

(INSERT FIGURE 2 HERE)

5. Methodology and database

To test for the presence of the BWE we need to apply two different techniques. Firstly, it is necessary to estimate the cyclical sensitivity of the labor force. In a second stage, we test the existence of spatial patterns in the coefficients obtained. Finally, the third part of this section provides a brief description of the database.

5.1. The cyclical sensitivity of the labor force

To study the cyclical sensitivity of the labor force in Spain, we employ a panel dataset composed of the fifty Spanish provinces for the period 1977–2015. As we have explained before, we try to verify if the AWE, the DWE, or none of those effects prevail in these territories. For this, we rely initially on equation (17):

-

$$CPR_{it} = \alpha + \beta_i \cdot CUR_{it} + D_{2001} + \mu_i + \varepsilon_{it} \qquad (17)$$

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, finally, ε_{it} stands for the disturbance term. In this case both, α and are μ_i are fixed constants and we need additional restrictions to estimate them. One way to do that is to introduce the restriction $\sum_{l=1}^{n} \mu_i = 0$. Then, the fixed effect μ_i represents deviations from the mean intercept α.[13] By this procedure we obtain fifty estimations of the cyclical sensitivity of the labor force (β_i), one for each Spanish province.

The main problem lies in obtaining the CPR_{it} and the CUR_{it}. This is because the cyclical component of the variables cannot be observed, and it has to be estimated. The economic literature provides several methods for obtaining these cyclical components; one of these is the Hodrick–Prescott filter (Hodrick and Prescott, 1997) (HP, hereafter). 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 value is very common

[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).

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

At this point, it is also convenient to refer to studies that question 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 (monthly, quarterly, yearly etc.). 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, hereafter) is used as an alternative to obtain the cyclical component.[14] Regarding the second limitation, it is worth clarifying that this work is not aimed at making predictions, but focuses on the analysis of the cyclical sensitivity. Finally, and with regard to the choice of λ, the cyclical component has been 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. Anyhow, it is worth pointing out that some estimates applying the Hamilton filter have been carried out to obtain the cyclical component of the time series and the outcomes are similar to those of our baseline models.[16]

Once equation (17) is estimated, 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 dominates the other.

[14] This method is based in 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 way, we extract both the trend component of the data previously mentioned and the disturbance term, which is identified with the cyclical component

[15] It should be mentioned that there are econometric alternatives to these two methods, such as the Baxter-King filter (Baxter and King, 1999) and, other "more complex" strategies (Phillips curve, Kalman filter, etc.).

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

To avoid various econometric problems (spurious correlation etc.) it is necessary to test if the cyclical components of the PR and the unemployment rate are stationary. For this reason, we have carried out several unit-root panel data tests (table A1 in the Appendix).[17] The results let us conclude that our cyclical components, obtained with the HP (for both λ parameter values) and the QT procedure, are stationary.

5.2. Spatial analysis of the cyclical sensitivities

Once the fifty cyclical coefficients of the PR at a provincial level are estimated, the next step is to carry out the spatial analysis to test for the presence of the BWE. First, it is necessary to define a neighborhood criterion by means of a weight spatial matrix. Further, to check the robustness of the results we opted to conduct the analysis employing various alternative spatial weight matrixes.[18] To detect if there is global spatial dependence, we compute the Global Moran´s I, (Moran, 1948) which is defined as follows:[19]

$$I = \frac{N}{S_0} * \frac{\sum_{i,j}^{N} SW_{i,j}\,(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2} \qquad (18)$$

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 $\sum_i \sum_j w_{ij}$, and, finally, $\bar{x}$ corresponds to the sample mean of variable x. The Global Moran's I takes values between 1 and -1. If the values are close to 1, there is positive

[17] These panel tests, basically, are an extension of the ADF test ("Augmented Dickey–Fuller") applied to a panel data structure. In the case of the Harris–Tzavalis test, the Levin–Lin–Chu test and the Breitung test, it is assumed that the unit-root procedure is homogeneous. By its part the Im–Pesaran–Shin test allows to examine 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.

spatial dependence, and there is negative spatial dependence if the values are close to -1.[20] It is important to point out that the results of the spatial dependence analysis are used as an indicator of the BWE about the individuals' decision to participate in the labor market, i.e., AWE and DWE are also the result of a social effect associated with the behavior observed in the environment.

5.3. Database

For the purpose of this research, we need annual information of the unemployment rate and the LFP. We use annual data taken from the Labor Force Survey (Encuesta de Población Activa, EPA) drawn up by the National Statistics Institute (Instituto Nacional de Estadística, INE) for the fifty Spanish provinces (NUTS-3). The information used focuses on the period 1977–2015. Finally, to provide more detailed information concerning the variables used, Appendix (table A2) offers some descriptive statistics.

6. Results

This section is divided into two sub-sections. Firstly, we show the results obtained for the cyclical sensitivity of the labor force. Secondly, we present the main results for the spatial analysis.

6.1. Results for the AWE and the DWE

[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.

Table 2 exposes the results of estimating equation (17) when the cyclical components of the variables are obtained by the application of the HP filter with λ=400. Also, and because of the length of the period, we consider that it could be interesting to analyze what happens in two shorter periods: 1977–1996 and 1997–2015. In this way, we can test more precisely the effect of the business cycle over the LFPRs in Spain and the robustness of the results. The main reasons to split the full period into these two sub-periods are the following: firstly, each of these two sub-periods represents, approximately, a complete economic cycle; secondly, it is a well-known fact that, during the last years of the nineties, Spain experienced a large wave of immigration (Carrasco et al. 2008). This phenomenon generated important changes in the economic dynamics of the Spanish labor market (Farré et al. 2011). Finally, the length of these two sub-periods is about equal (twenty and nineteen years, respectively). Columns 2 and 3 in table 2 include the estimations of these two sub-periods.

The results show twenty-two statistically significant coefficients for the period 1977–2015, and the DWE prevails over the AWE in nineteen of them. In the case of the first sub-period (1977–1996), twenty-seven provinces present results that are statistically significant, with the DWE as 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 λ= 100 (table A3 in the Appendix). For the whole period, the results are quite similar to those obtained before, with a great number of statistically significant results, especially when we employ the QT procedure. The principal effect is the DWE, which is present in thirty provinces out of a total of thirty-four provinces that have statistically significant results. For the two sub-periods, the DWE also predominates in most of the provinces were the results are statistically significant. We have only found 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 λ=100, we obtain the same results. The DWE also predominates for the whole period and for the first sub-period.

Figure A1 in the Appendix includes two scatterplots that confirm the robustness of the estimations. The results obtained by the HP filter with λ = 400 and λ = 100 are positively correlated with a R^2 equal to 0.85 and a correlation coefficient (ρ) of 0.92. Also, the same pattern is maintained when we observe the relationship between the estimations of the HP λ = 400 and the QT procedure; in this case the R-squared is 0.79 and ρ is 0.89.

(INSERT TABLE 2 HERE)

6.2. Spatial analysis of the cyclical sensitivities

Once we have estimated the cyclical sensitivities, 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 that expressed in equation (16). To begin the analysis, it is necessary to establish a neighborhood criterion, such as either the k-nearest neighbors (Knn) or the inverse distance (ID).[21] In this paper we use ten different Knn matrices ($K = 1 \dots 10$) where the specification of the spatial weights is.

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

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

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 the 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 matrixes. The analysis of the sub-periods indicates that, between 1977 and 1996, we only find a positive spatial dependence either when we consider less than three neighbors or when the distance is more penalized. From 1997 to 2015, there is once again a positive spatial dependence for all the matrixes, 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 were used: 5 nearest neighbors and inverse distance 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 A2 in the Appendix).

(INSERT TABLE 3 HERE)

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 λ =100 (table A4 in the Appendix). In the case of the QT procedure, the results show positive spatial dependence both for the whole period

[22] We also perform the same analysis 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 show in table 3. Detailed results are available from the authors upon request

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 quite similar to those obtained with λ=400. The spatial dependence is present both for the entire period and for the two groups of matrixes. The analysis by sub-periods only shows spatial dependence between 1997 and 2015 and for some spatial matrixes. Figures 3 and 4 present the scatter plots of the Global Moran's I for the HP filter (λ=400), when three Knn matrixes (K=1, 3 and 5) and three ID matrixes (α=1, 2 and 3) are used. The spatial correlation shown in figures 3 and 4 is consistent with the interaction presented in figure 2 and allows us to confirm the presence of the BWE. This corroborates the existence of a "social effect", which causes that the cyclical sensitivity of the LFP in one territory is influenced by what happens in its neighboring regions.[23]

(INSERT FIGURE 3 AND 4 HERE)

The next step in the spatial analysis is to study the evolution of the spatial dependence before changes in neighborhood parameters. As we explained before, each neighborhood criterion includes ten different levels. Depending on the spatial correlation in each level, it is possible to 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 5 and 6 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 happens in the nearest territories. As we increase the number of provinces that we consider "neighbors", the social effect tends to disappear.[24]

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

(INSERT FIGURE 5 AND 6 HERE)

7. Extensions and sensitivity analysis.

Although the results presented in the previous section already show the existence of a BWE, it is necessary to broaden the analysis in order to discard other possible explanations. To this end, some additional specifications are presented that will allow confirmation of the influence of the closest environment over the cyclical sensitivity of the PR.

7.1. Population composition effect.

The first point to take into account is the possible influence of the population characteristics in each territory when explaining the observed spatial dependence. To analyze this effect four additional variables are included in equation (17) to indicate the composition by gender and age in each territorial unit. The new model is expressed as follows:

$$CPR_{it} = \alpha + \beta_{i1} \cdot CUR_{it} + \beta_2 D_{2001} + \beta_3 F + \beta_4 A1 + \beta_5 A2 + \beta_6 A3 + \mu_i + \varepsilon_{it} \qquad (19)$$

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

(INSERT FIGURE 7 HERE)

The results presented in figure 7 show that the spatial dependence in the cyclical sensitivity is maintained, although with somewhat lower values of the Moran's I. This 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 in the Appendix).

To deepen the demographic aspects, the cyclical sensitivity of the activity rate is also estimated separately for males and females (table A5 in the Appendix). 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 A3 and A4 in Appendix). This result is coherent with the social effects found in the labor supply of women by Woittiez and Kapteyn (1998) or Maurin and Moschion (2009).

7.2. Spatial Models.

In addition to the population composition, there may be other sources of spatial dependence that could be affecting the BWE. In this sense, it is logical to assume that the dependence should be related to the variables not included in the model and would be detected by estimating a spatial error model (SEM) such as the one presented in equation (20):

$$CPR_{it} = \alpha + \beta_{i1} \cdot CUR_{it} + \beta_2 D_{2001} + \mu_i + \varepsilon_{it} \qquad (20)$$

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

From the results obtained in this new estimation, the spatial correlation of the cyclical sensitivity is tested again with the two previous weight matrices (inverse distance and 5 nearest neighbors). The results presented in figure 8, as in the previous case, show that the spatial correlation decreases slowly. However, a statistically significant BWE is still maintained even when spatial dependence in the errors is also detected (table A5 in the Appendix includes the cyclical sensitivity coefficients and the lambda parameter related to the spatial dependence in the error term).

(INSERT FIGURE 8 HERE)

Additionally, we have also included the estimation of a spatial lag model or spatial autoregressive model (SAR). This specification includes an additional term obtained as the product of the spatial weight matrix and the cyclical component of the PR, as shown in equation (21):

$$CPR_{it} = \alpha + \rho WCPR_{it} + \beta_{i1} \cdot CUR_{it} + \beta_2 D_{2001} + \mu_i + \varepsilon_{it} \quad (21)$$

In this case, when the global spatial correlation test is performed, the Moran I is not significantly different form zero (figure 9). This result makes sense if we take into account that the spatial dependence in the cyclical component is already included in the spatial lag coefficient of the dependent variable which is positive and significant (table A5 in the Appendix includes cyclical sensitive coefficients, the Rho parameter and the spatial lag coefficient of the dependent variable).

(INSERT FIGURE 9 HERE)

7.3. Methodological changes and labor reforms.

Other aspects to take into account when analyzing 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 took

place in 1999, 2001 and 2005 (the 2001 change was already taken into account in previous specifications due to its special relevance). As for labor reforms, Spain is characterized by having frequent legislative changes that affect the labor market. However, the most ambitious reforms since the approval of the Workers' Statute (1980) were carried out in 1984, 1994, 2010 and 2012. To take into account all these possible effects, 8 dummy variables are included in the model (equation 22).

$$CPR_{it} = \alpha + \rho WCPR_{it} + \beta_{i1} \cdot CUR_{it} + \beta_2 D_{1980} + \beta_2 D_{1984} + \beta_2 D_{1994} + \beta_2 D_{1999} + \beta_2 D_{2001} + \beta_2 D_{2005} + \beta_2 D_{2010} + \beta_2 D_{2012} + \mu_i + \varepsilon_{it} \quad (22)$$

Where each D_i represents the methodological change or labor reform made in year i. Once the equation (22) is estimated, the global spatial correlation test on the β_{i1} is repeated using the inverse distance and the 5 nearest neighbors matrix. The results of this analysis are presented in figure 10 and once again reaffirm the robustness of our conclusions with a statistically significant BWE (the estimated values for the cyclical sensitivity are shown in table A5 of the Appendix).

(INSERT FIGURE 10 HERE)

7.4. Quarterly data.

Finally, we also analyze if the spatial dependence is determined by the data structure. To deal with this issue we re-estimate equation (17) by using quarterly data. The fact of using this type of data has additional consequences. On the one hand, it is necessary to deseasonalize the time series and to do that the x-12 ARIMA method has been used. On the other hand, to obtain the cyclical component of the series we have to modify the smoothing parameter of the HP filter. The empirical literature in this issue is unanimous and it is advisable to use λ=1600 (Ravn and Uhlig,

2002). The model also includes a three lags structure for both, the dependent variable and the independent ones. In this way, 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 a quarter to take effect are considered. The correct specification in this case is the one presented below:

$$CPR_{it} = \alpha + \sum_{j=1}^{3} \psi_i^j CPR_{it-j} + \beta_{i1} \cdot CUR_{it} + \sum_{j=1}^{3} \beta_{i1}^j CUR_{it-j} + \beta_2 D_{2001} + \mu_i + \varepsilon_{it} \quad (23)$$

The fact of including a lag structure in the dependent variable and in the explanatory ones provides two types of cyclical sensitivity: one of short term (β_i^S) and another one of long term (β_i^L) that are defined as follows:

$$\beta_i^S = \beta_{i1} + \sum_{j=1}^{3} \beta_{i1}^j \quad (24)$$

$$\beta_i^L = \beta_i^S / (1 - \sum_{j=1}^{3} \psi_i^j) \quad (25)$$

In this point the spatial correlation of β_i^S and β_i^L is tested again in order to analyze if the data structure modifies the results. As in the previous cases, the spatial dependence is maintained with both matrixes (5 nearest neighbors and inverse distance) which confirms that the yearly data structure does not determine the presence of the BWE. It can also be checked that the value and the significance of the Moran's I are quite similar in both the sensitivity of short and long term (figures 11 and 12)[25]

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

(INSERT FIGURES 11 AND 12 HERE)

8. Discussion and policy implications

Once we have offered empirical evidence of the existence of the BWE, in the following paragraphs we will comment on the economic policy implications that it generates. We organize the economic policy implications and recommendations within three different categories: firstly, those economic policy proposals that have to do with the fact that we detect important heterogeneities in the cyclical response of the LFP in different spatial units; secondly, those economic policy consequences related to the finding that there is a significant spatial dependence in the LFP cyclical pattern of Spanish NUTS-3 units (i.e. the significance of the BWE); finally, some policy suggestions as a result of the particular administrative hierarchy among NUTS-2 and NUTS-3 units in Spain.

To begin with, 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, finally, there are also spatial units where both effects offset each other. In general terms, this means that the economic measures should be carried out while bearing in mind the territorial context, so the policy makers should not design economic policies that have the same intensity of effect in all the regions. In other words, different territories need specific policies that focus on the labor market dynamics of each territory. Being more specific, this spatial heterogeneity has implications for the implementation of both aggregate demand policies and policies on the supply side.

As mentioned before, during a downturn, if the DWE dominates the AWE then 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, more active labor market policies (e.g. training schemes, public employment services, etc.) 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 may serve as a guideline for policy makers to better distribute the limited fiscal budget in different business cycle phases, according to the previous discussion, enhancing in this way the efficiency of economic policy execution. Put differently, policy makers should devote less budgetary resources to spatial units with a predominant AWE during recessions than suggested by the measured unemployment rate and more to those with a prevailing DWE, and reverse this economic policy pattern during expansions. This economic policy rule would be efficiency-enhancing as long as the fiscal budget remained unchanged at the aggregate level.

Secondly, our evidence shows a significant spatial dependence in the cyclical sensitivity of LFP, that is, what we name the BWE. This means that 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 take into account 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 issue is that regions cannot be studied in isolation from each other but interact with their neighbors. This statement is, however, 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, as it seems to be according to our findings, we might expect that the DWE and the AWE will spread across neighboring spatial units during economic upturns and downturns. In this way, the overstatement or understatement of true unemployment across spatial units would be "contagious" and, consequently, the correct economic policy and, even more importantly, the correct intensity of such a policy should be determined by adopting a supra-provincial perspective.

The third and last group of economic policy implications has to do with the particular administrative division of the Spanish territory NUTS-3 units in Spain (provinces) 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, La Rioja, Murcia and Navarre) there is a coincidence 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 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 a much less important part of it.[26] This fact entails that autonomous communities play 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 in the economic policies among different neighboring NUTS-2 regional governments are required. This is so since, as previously

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

pointed out, there are important spillover effects beyond the NUTS-2 level administrative division.

The previous issue could be tackled from two different points of view. In the first place, political leaders governing neighboring autonomous communities might take action seeking for higher coordination in their policies against unemployment spontaneously. In this vein, supra-regional committees managing labor market policies could be created, aiming to coordinate political efforts to minimize the true unemployment problem, by devising strategies accounting for the spillover effects. In the second place, if regional (NUTS-2) governments did not reach an agreement by themselves, the Spanish central government might take action 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 discuss with other regional representatives so as to make agreements seeking the aforementioned coordination; (2) the Spanish central government might take direct action in order to solve this question. In other words, it could create a political institution depending on the Ministry of Labor (e.g. a Secretary of State or a General Directorate) devoted exclusively to produce coordination among different regional labor market policies.

9. Conclusions

The key issue of this paper is to test whether the relationship between the business cycle and LFP in any given area may be affected by the behavior of its neighbors. To do that, we first elaborate a microeconomic decision model to conceptualize the AWE and the DWE. In a second stage, by means of 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, employing a panel dataset composed of the fifty Spanish provinces during the period 1977–2015. Also, due to 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 can conclude that the DWE dominates in most of the territories and periods where the coefficients are significant.

As our theoretical model shows, the cyclical sensitivity of the LFP in one area will be influenced by the behavior of its neighbors. To study that, after carrying out a macroeconomic aggregation process, we coined the BWE and tested it with standard spatial econometric techniques that we have 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", i.e. as we fix a laxer neighborhood criterion, the strength of the BWE decreases.

Our work posits some interesting economic policy implications that affect the outcome of the regional labor markets. First of all, policy makers should bear in mind that the regions do not all react in the same way to the economic shocks of the business cycle. Thus, the policies should to be applied while taking into account the economic dynamics of each zone, since the application of an economic policy with the same intensity for all the regions could lead to heterogeneous results. Another important issue is that the territories interact with their neighbors, so they are not fully "independent" of each other. In this way, the policy makers should focus their actions on spatial areas, instead of spatial units, due to the existence of social effects among the territories that might condition the outcome of the economic policies. Our work corroborates the idea that "social effects" play a key role in carrying out labor market policies. This implies that these phenomena could generate some kinds of effects that are not initially planned and that affect the economic dynamics of neighboring areas, even when the neighbors do not belong to the same territorial administration. That interdependence at the NUTS-3 level requires coordination in the economic policies among different neighboring NUTS-2 regional governments.

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Appendix

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.

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.

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
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
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.

Table A4. Global spatial dependence analysis (QT procedure and HP λ=100)

	QT			HP (λ=100)		
	1977–2015	**1977–1996**	**1997–2015**	**1977–2015**	**1977–1996**	**1997–2015**
Knn=1	0.379**	0.346**	0.401**	0.511***	0.194	0.246
Knn=2	0.453***	0.235**	0.488***	0.290**	0.091	0.125
Knn=3	0.445***	0.164*	0.502***	0.223**	0.030	0.119
Knn=4	0.425***	0.126*	0.476***	0.268***	-0.006	0.123
Knn=5	0.408***	0.115*	0.446***	0.214***	-0.050	0.087
Knn=6	0.405***	0.105*	0.449***	0.155**	-0.054	0.100*
Knn=7	0.349***	0.110**	0.381***	0.154***	-0.025	0.084
Knn=8	0.355***	0.122**	0.386***	0.140***	-0.014	0.111**
Knn=9	0.332***	0.099**	0.364***	0.108**	-0.049	0.094**
Knn=10	0.315***	0.099**	0.342***	0.093**	-0.050	0.082**
	1977–2015	**1977–1996**	**1997–2015**	**1977–2015**	**1977–1996**	**1997–2015**
ID (α=3)	0.342***	0.195***	0.372***	0.241***	0.074	0.100
ID (α=2.75)	0.330***	0.178***	0.360***	0.223***	0.065	0.093
ID (α=2.50)	0.314***	0.161***	0.345***	0.203***	0.055	0.087
ID (α=2.25)	0.295***	0.142***	0.324***	0.181***	0.044	0.080*
ID (α=2)	0.270***	0.121***	0.299***	0.158***	0.033	0.072*
ID (α=1.75)	0.240***	0.100***	0.268***	0.133***	0.021	0.063*
ID (α=1.50)	0.206***	0.078***	0.232***	0.107***	0.011	0.053**
ID (α=1.25)	0.168***	0.056***	0.191***	0.081***	0.001	0.043**

ID (α=1)	0.128***	0.037**	0.147***	0.057***	-0.006	0.031**
ID (α=0.75)	0.087***	0.019***	0.103***	0.034***	-0.012	0.018***

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.

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	0.119*	-0.035	0.005	-0.016	-0.039	-0.093
Albacete	0.069*	0.072	-0.061	0.077*	0.105***	0.049	0.057	0.087**	0.032	0.086
Alicante	0.010	-0.089	-0.035	-0.029	0.011	-0.047	-0.043	-0.017	-0.037	-0.094
Almeria	-0.028	0.049	-0.124***	-0.080*	-0.044	-0.105**	-0.096**	-0.062	0.050	0.127
Asturias	0.089	0.051	-0.041	0.057	0.126**	0.007	0.038	0.106*	0.071	0.191
Avila	0.041	0.117*	0.026	0.106**	0.187***	0.081*	0.100**	0.113**	-0.028	-0.070
Badajoz	0.007	0.097	0.015	0.095**	0.116***	0.022	0.041	0.082*	0.012	0.028
Balearic Islands	0.042	-0.022	-0.111*	-0.018	0.013	0.028	-0.018	0.020	0.046	0.131
Barcelona	0.010	0.016	-0.106**	-0.002	0.034	0.017	0.005	0.020	0.042	0.125
Burgos	-0.038	-0.040	-0.096	-0.043	0.080	-0.077	-0.031	-0.007	-0.053	-0.122
Caceres	0.087*	0.184***	0.069	0.139***	0.206***	0.102**	0.137***	0.198***	0.106	0.299
Cadiz	0.110***	0.152***	-0.067	0.149***	0.152***	0.079**	0.095***	0.140***	0.021	0.055
Cantabria	-0.056	-0.080	-0.181**	-0.096	0.005	-0.123**	-0.092	-0.042	0.018	0.045
Castellon de la Plana	-0.076	-0.044	-0.159***	-0.099*	-0.058	-0.112**	-0.106**	-0.089*	-0.044	-0.089
Ciudad Real	-0.023	-0.094	-0.039	0.054	0.116**	-0.009	0.019	0.031	0.046	0.083
Cordoba	0.026	0.137**	-0.076*	0.085**	0.117***	0.012	0.046	0.082*	0.066	0.138
Corunna (A)	0.200***	0.055	0.014	0.191***	0.230***	0.125*	0.146**	0.243***	0.040	0.161
Cuenca	-0.068	0.006	-0.090	0.109*	0.147***	0.046	0.056	0.081	0.023	0.048
Girona	-0.137**	-0.211**	-0.233***	-0.215***	-0.167***	-0.205***	-0.214***	-0.164**	0.000	0.000
Granada	0.022	0.082	-0.098**	0.066*	0.101***	0.026	0.039	0.067*	0.030	0.095
Guadalajara	-0.080	-0.122*	-0.100	-0.108*	0.008	-0.133**	-0.086	-0.082	0.046	0.118
Guipuzcoa	-0.023	-0.108	-0.111	-0.078	0.043	-0.087	-0.055	-0.058	0.031	0.082

Huelva	0.132***	0.192***	0.044	0.140***	0.143***	0.075*	0.092**	0.137***	0.084	0.170
Huesca	0.010	0.004	-0.069	0.002	0.102	0.006	0.022	0.030	-0.011	-0.021
Jaen	0.022	0.231***	-0.024	0.112***	0.142***	0.062	0.080**	0.102***	-0.002	-0.005
Leon	0.012	0.063	-0.044	0.104	0.196***	0.035	0.089	0.136**	0.057	0.142
Lleida	0.031	-0.087	-0.227**	-0.060	0.032	-0.037	-0.038	-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***	0.391***	0.249***	0.276***	0.369***	0.043	0.139
Madrid	-0.018	-0.109	-0.171***	-0.070	0.051	-0.108**	-0.054	-0.058	-0.016	-0.028
Malaga	0.088**	0.188***	-0.054	0.095**	0.103***	0.029	0.051	0.087**	0.011	0.028
Murcia	0.007	-0.016	-0.135***	-0.028	0.018	-0.056	-0.044	-0.018	0.021	0.049
Navarre	-0.064	-0.139	-0.117	-0.078	0.041	-0.094	-0.059	-0.066	-0.029	-0.055
Orense	-0.027	0.000	-0.163**	0.022	0.042	-0.044	-0.037	0.029	0.000	-0.001
Palencia	0.043	-0.033	0.033	0.121**	0.213***	0.110**	0.128**	0.126**	0.076	0.224
Palmas (Las)	-0.016	0.01	-0.172***	-0.057	-0.078*	-0.108**	-0.095**	-0.068	0.011	0.027
Pontevedra	0.046	-0.002	-0.102	0.007	0.059	-0.055	-0.037	0.054	0.056	0.185
Rioja (La)	-0.072	-0.080	-0.107	-0.070	0.033	-0.089	-0.068	-0.080	0.003	0.007
Salamanca	0.073	0.085	0.008	0.148**	0.233***	0.119**	0.136**	0.191***	0.108	0.208
Segovia	-0.036	0.087	-0.052	0.007	0.167**	0.002	0.047	0.041	0.009	0.019
Seville	0.011	0.027	-0.101	0.034	0.045	-0.064	-0.032	0.010	0.028	0.078
Soria	-0.141	0.070	-0.128***	-0.021	0.167*	-0.030	0.021	0.013	-0.026	-0.067
Tarragona	-0.105*	0.072	-0.224**	-0.158***	-0.105*	-0.181***	-0.165***	-0.143**	-0.097	-0.169
S C Tenerife	0.127**	-0.200**	-0.194***	0.096*	0.058	0.047	0.039	0.095*	0.009	0.023
Teruel	-0.067	-0.084	-0.159*	0.014	0.090	-0.026	-0.007	0.003	-0.081	-0.179
Toledo	-0.002	0.052	-0.153***	0.024	0.117**	-0.033	0.008	0.036	-0.014	-0.038
Valencia	-0.013	-0.010	-0.192***	0.002	0.032	-0.042	-0.027	-0.024	-0.008	-0.021
Valladolid	-0.108*	-0.156**	-0.169**	-0.141**	-0.015	-0.187***	-0.137**	-0.109*	-0.056	-0.162
Vizcaya	-0.007	-0.082	-0.080	-0.017	0.118**	-0.023	0.023	0.012	-0.031	-0.078
Zamora	-0.194***	0.021	-0.280***	-0.128**	-0.019	-0.165***	-0.122**	-0.053	0.038	0.087
Saragossa	0.017	-0.026	-0.101*	0.007	0.081	-0.010	0.014	0.013	0.023	0.062

λ	0.559***	1.048***					
ρ			0.518***	1.010***			

*, **, and *** show s statistical significance at 10%, 5%, and 1% levels, respectively.
In the last two columns the level of significance is not included because the results are obtained by using expressions (24) and (25)

Figure A1. Scatterplot diagrams of the relationship between the cyclical sensitivities obtained by the HP method (λ=400), HP method (λ=100) and the QT procedure

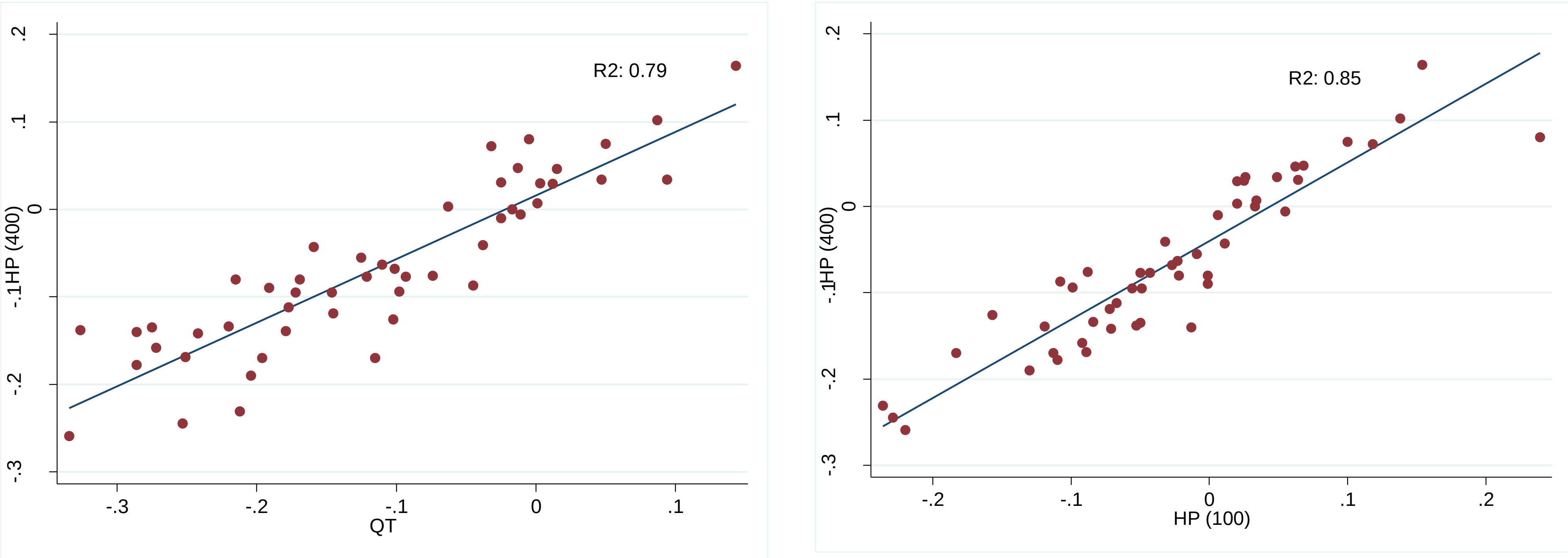


Figure A2: Local spatial dependence test (1977–2015) (HP λ=400)

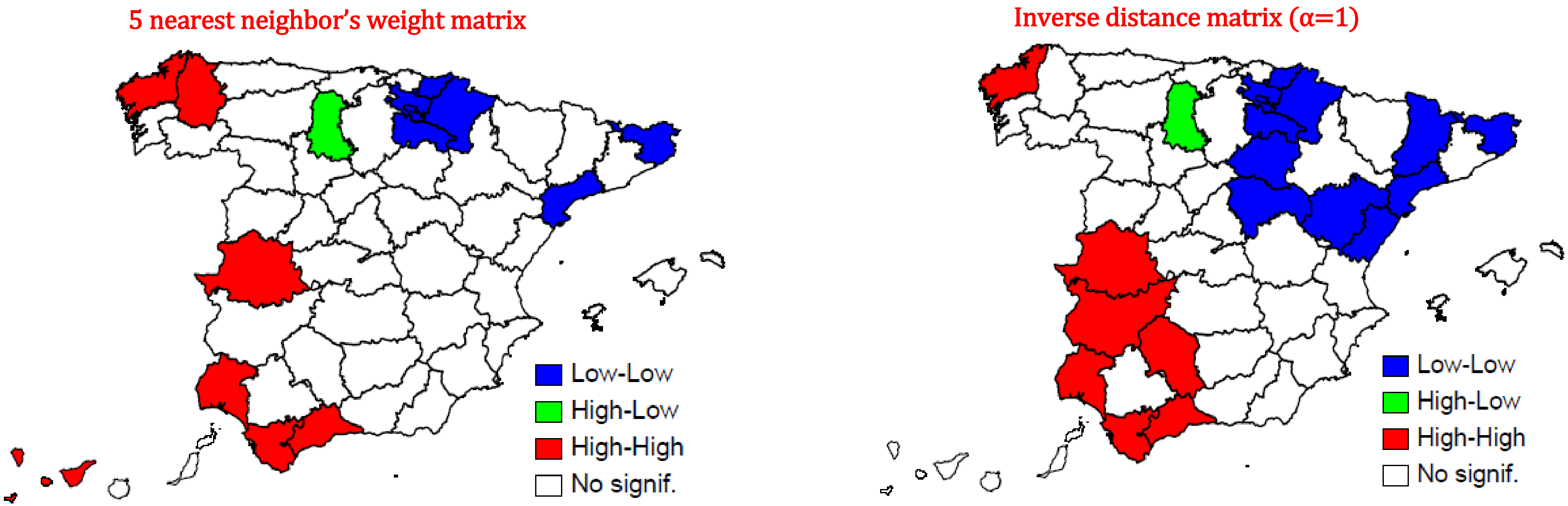
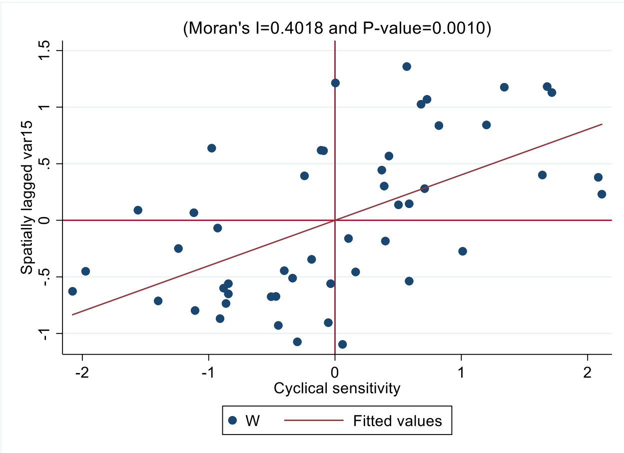


Figure A3. Global Scatterplot diagrams of Moran's I: Females (1977–2015) (HP λ=400)

5 nearest neighbor's weight matrix



Inverse distance matrix (α=1)

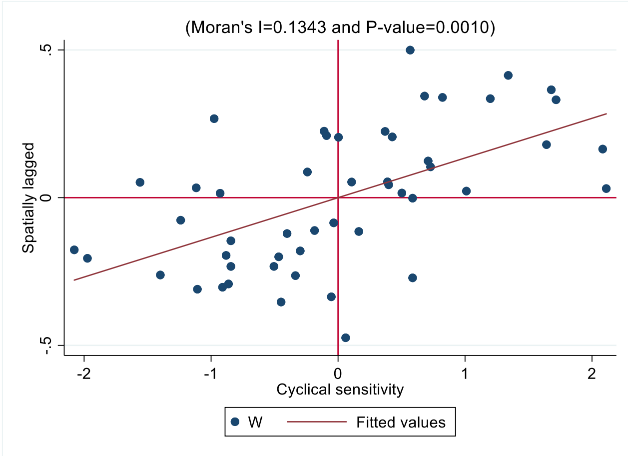
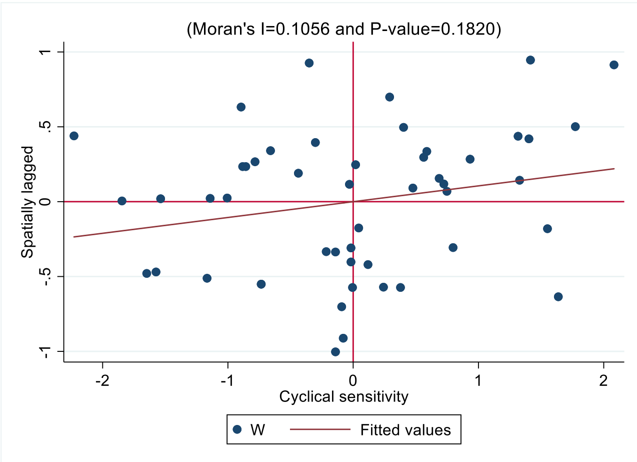


Figure A4. Global Scatterplot diagrams of Moran's I: Males (1977–2015) (HP λ=400)

5 nearest neighbor's weight matrix



Inverse distance matrix (α=1)

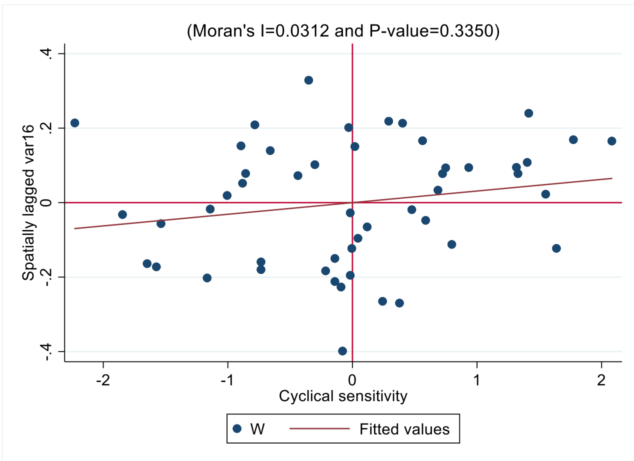


Figure 1. Set of alternatives for the worker

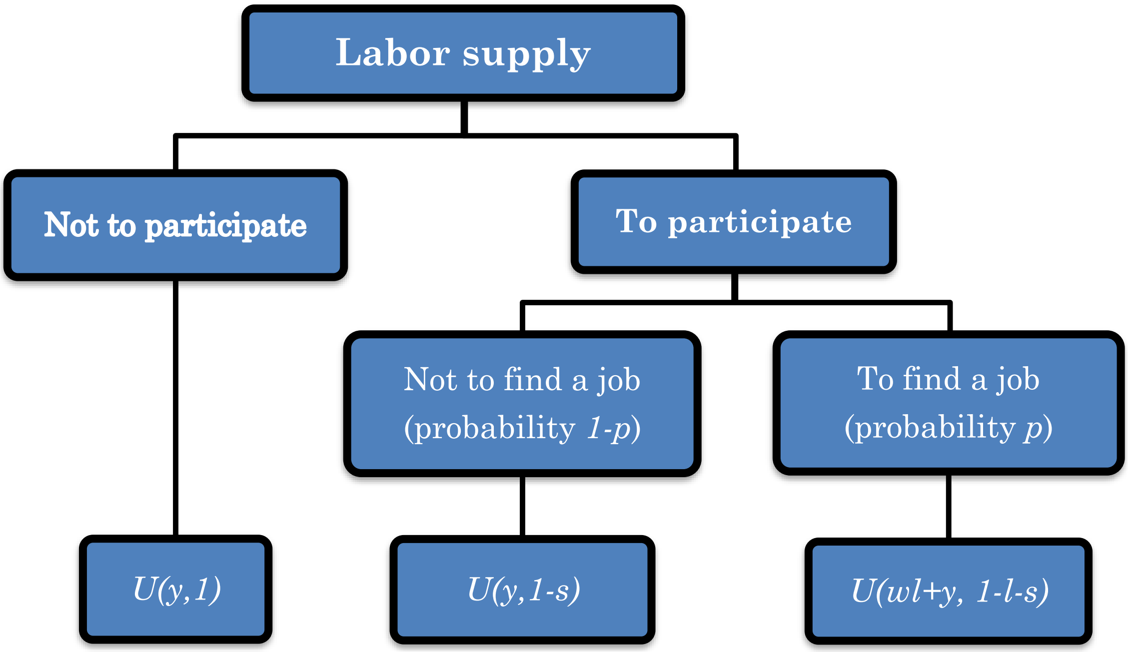


Figure 2. Cyclical PR sensitivity of an area as a function of the cyclical PR sensitivity of neighboring areas

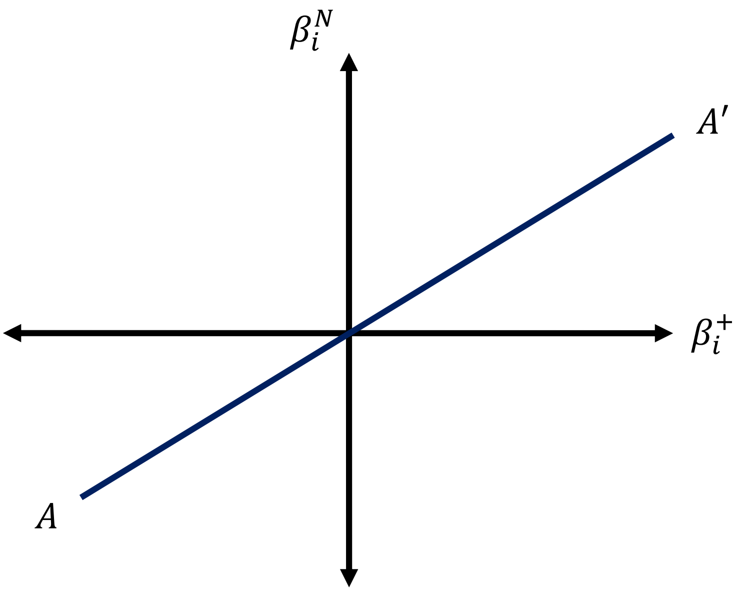


Figure 3. Global Scatterplot diagrams of Moran's I (HP λ=400) (1997–2015)

K=1 *K=5*

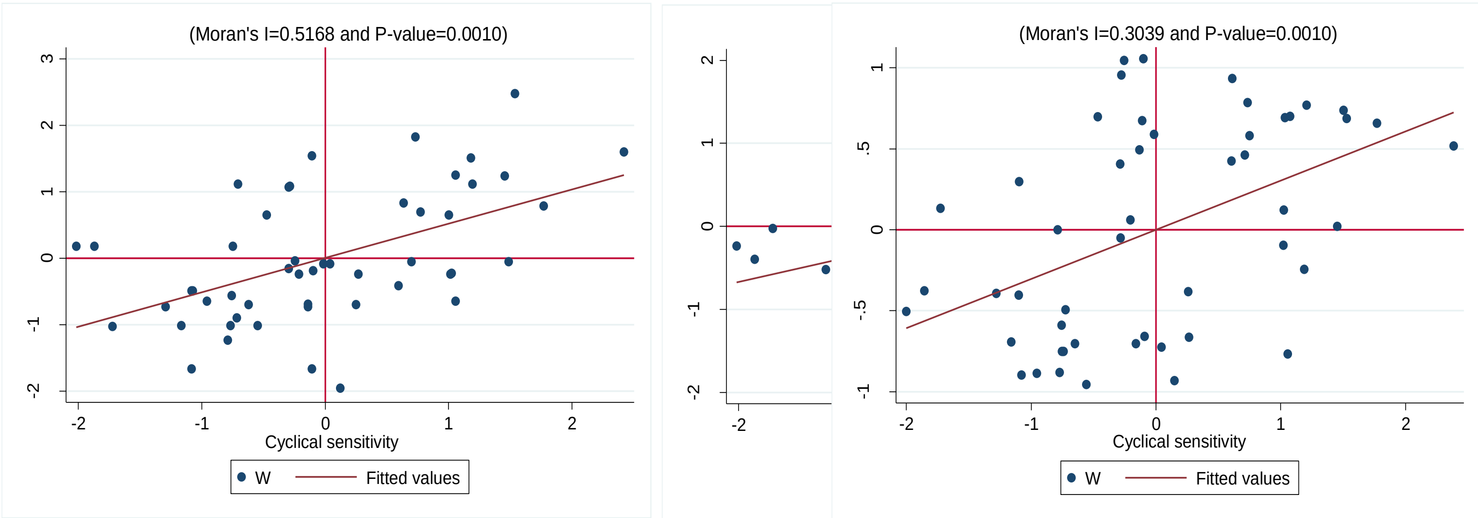


Figure 4. Global Scatterplot diagrams of Moran´s I (HP=400) (1997-2015)

α=1 *α=3*

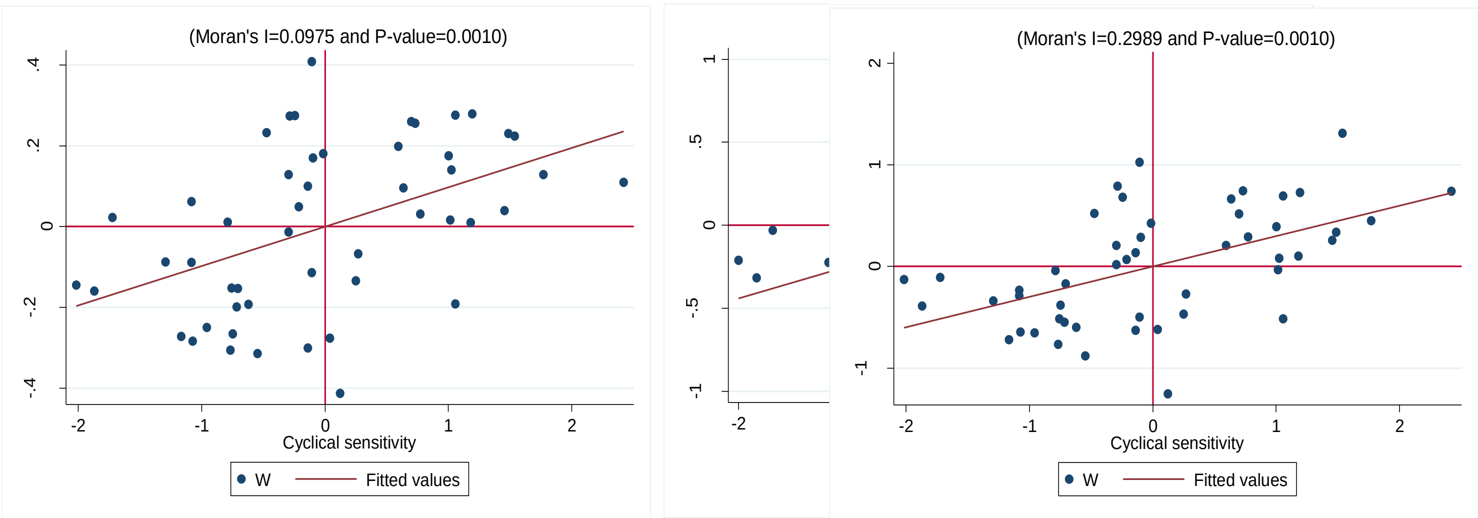


Figure 5. Evolution of the Global Spatial Dependence of the Knn matrixes (1977–2015) (HP λ=400)

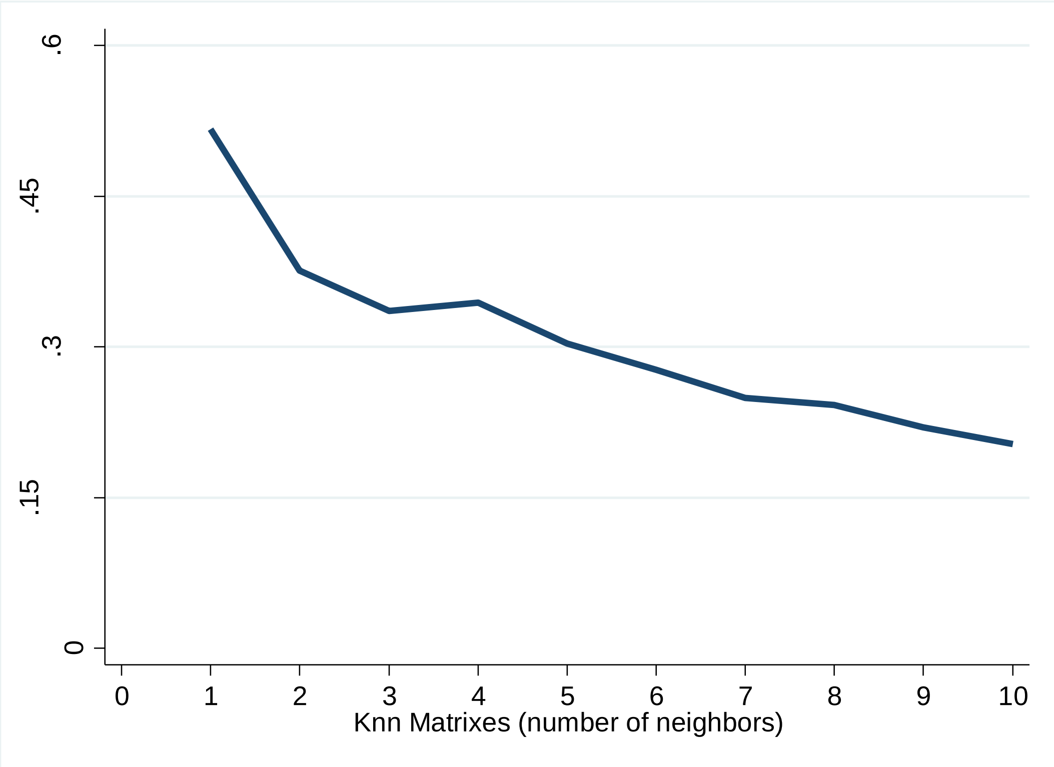
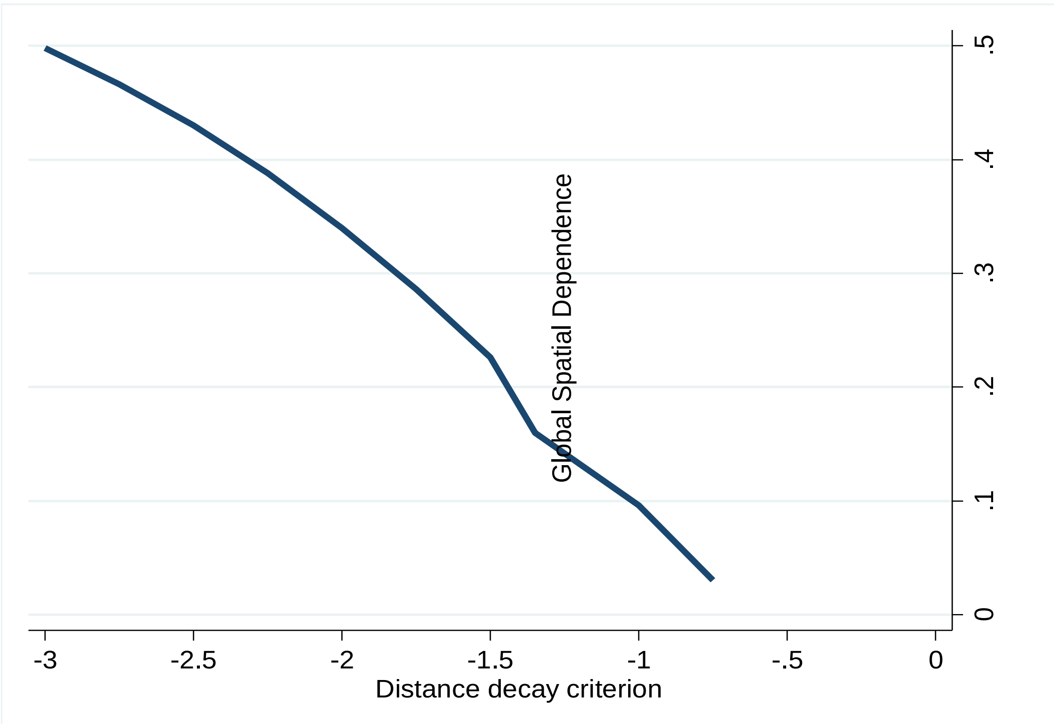


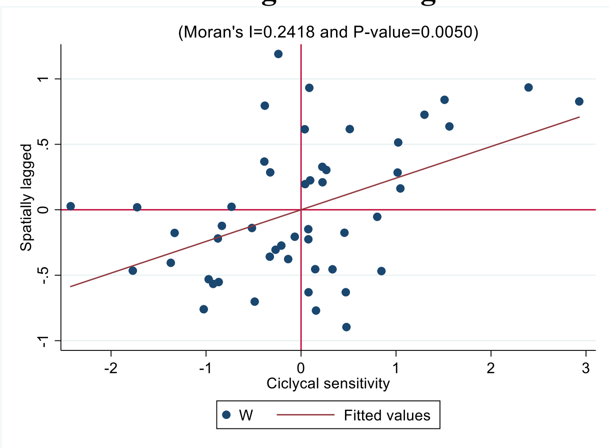
Figure 6. Evolution of the Global Spatial Dependence of the Inverse Distance matrixes (1977–2015) (HP λ=400)



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

Figure 7. 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)

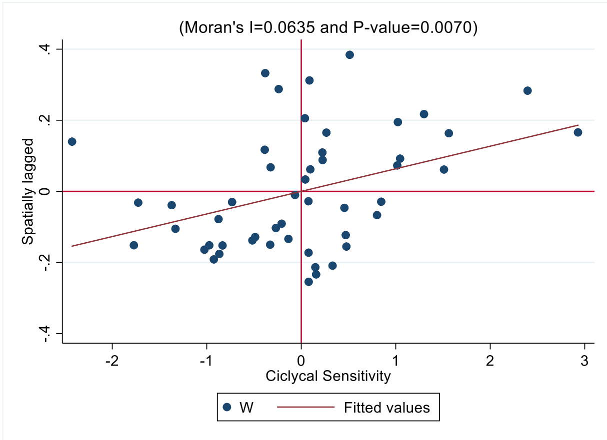
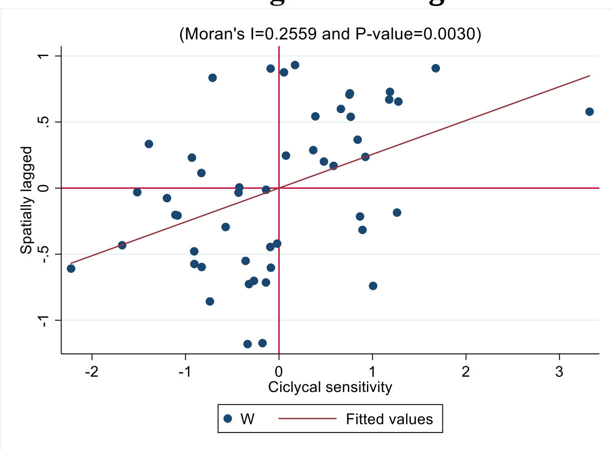


Figure 8. Global Scatterplot diagrams of Moran's I: SEM (1977–2015) (HP λ=400)

5 nearest neighbor's weight matrix



Inverse distance matrix (α=1)

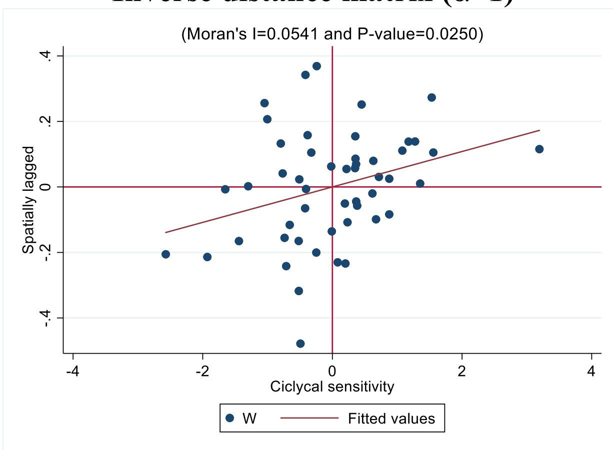
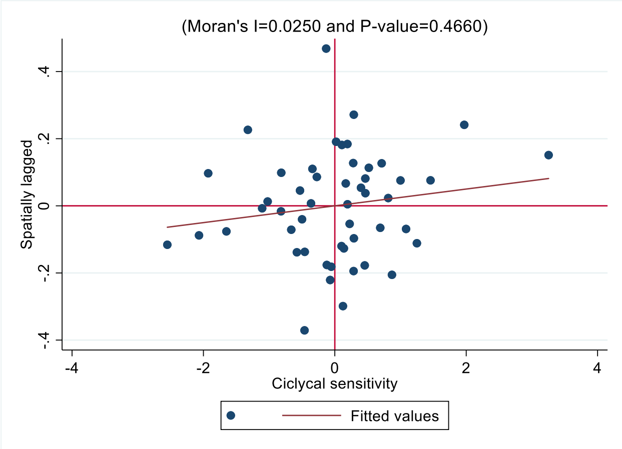


Figure 9. Global Scatterplot diagrams of Moran's I: SAR (1977–2015) (HP λ=400)

5 nearest neighbor's weight matrix



Inverse distance matrix (α=1)

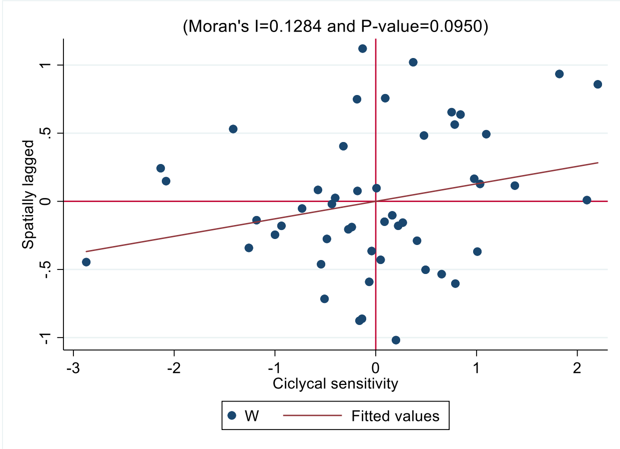
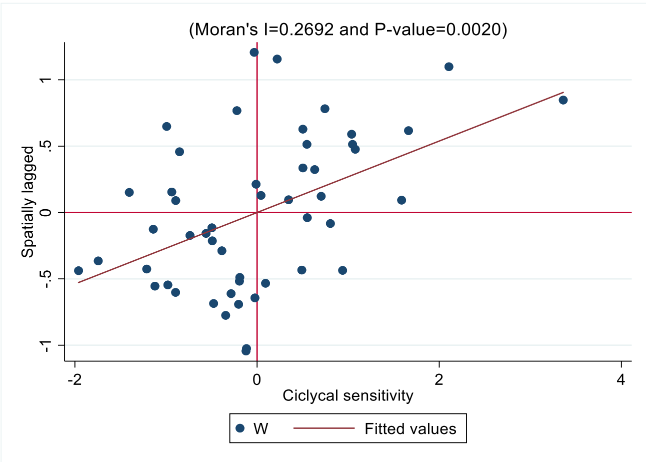


Figure 10. Global Scatterplot diagrams of Moran's I: Labor reforms and breaks in series (1977–2015) (HP λ=400)

5 nearest neighbor's weight matrix



Inverse distance matrix (α=1)

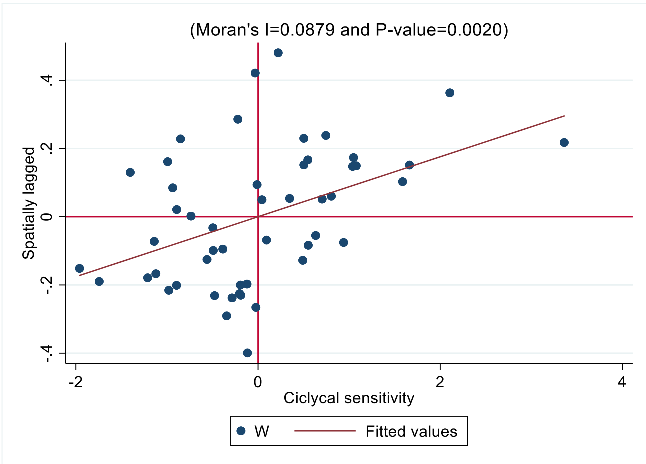
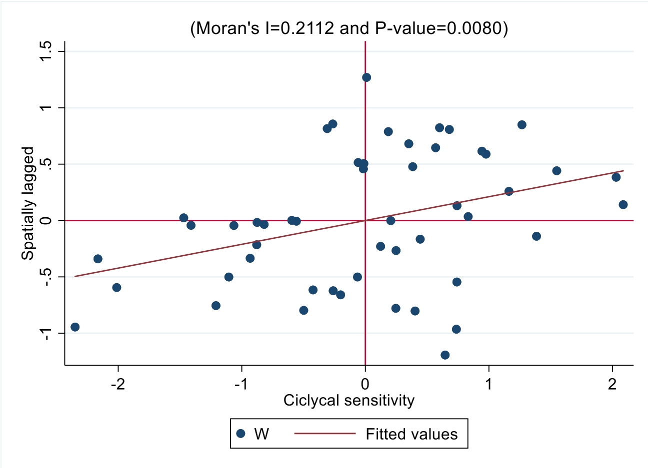


Figure 11. Global Scatterplot diagrams of Moran's I: Short term elasticity (1977–2015 quarterly) (HP λ=400)

5 nearest neighbor's weight matrix



Inverse distance matrix (α=1)

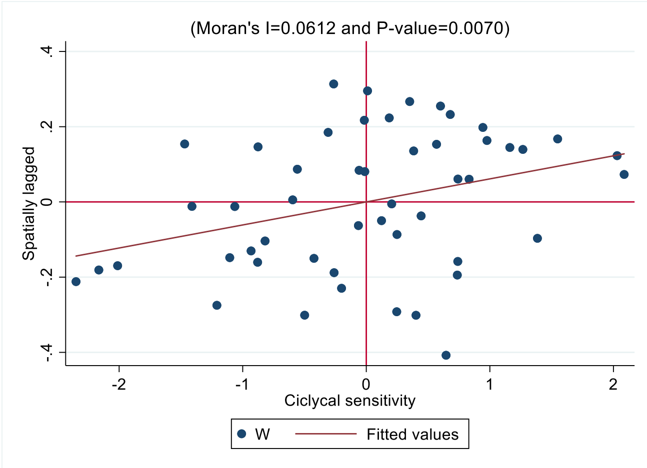
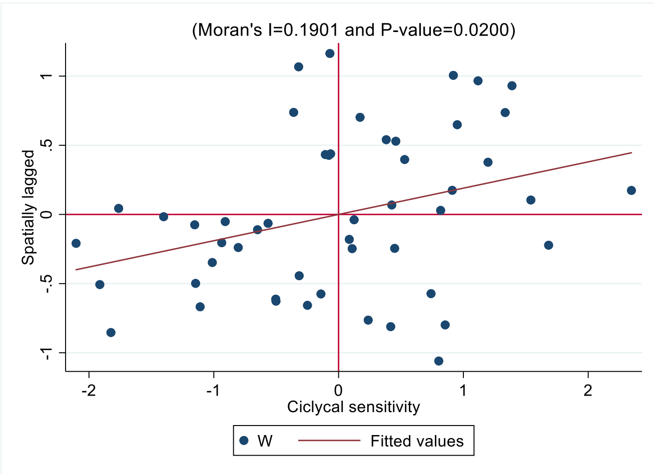


Figure 12. Global Scatterplot diagrams of Moran's I: Long term elasticity (1977–2015 quarterly) (HP λ=400)

5 nearest neighbor's weight matrix



Inverse distance matrix (α=1)

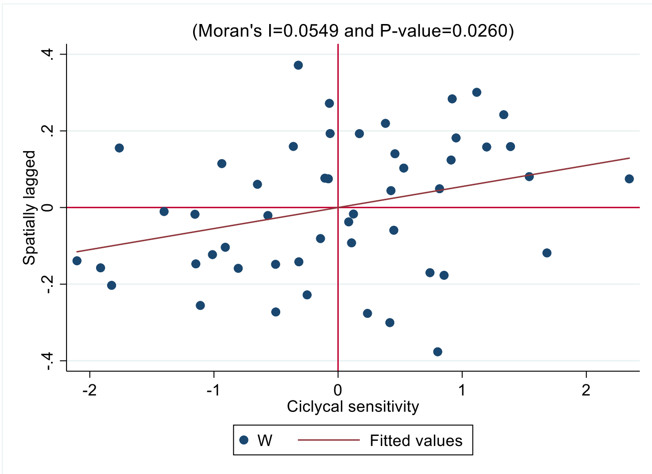


Table 1. LFPR and spatial effects in the regional labor markets

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

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.

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

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.