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Natural and cyclical unemployment: a stochastic frontier decomposition and economic policy implications

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Abstract

The main goal of the present work is to split effective unemployment into two components, one dealing with the natural rate of unemployment, and another with cyclical unemployment. With this purpose in mind, an estimation of stochastic cost frontiers is performed where natural unemployment is identified as a lower limit and cyclical unemployment as the deviation of effective unemployment with regard to that limit. To achieve this purpose, information is used from the 17 autonomous communities in Spain over the period spanning 1982 to 2013. Results evidence a greater importance of the natural component as the principal determinant of effective unemployment at a regional scale. The latter part of the work compares stochastic frontier estimations to those obtained when applying univariate filters, which are in widespread use in economic literature. The main conclusion to emerge is that the proposed decomposition modifies the weight distribution amongst the various types of unemployment, increasing the importance of cyclical unemployment. This finding has significant implications for economic policy, such as the existence of a greater margin for aggregate demand policies in order to reduce cyclical unemployment, particularly during growth periods.

Key words: Natural Unemployment, Cyclical Unemployment, Labor Market, Stochastic Frontiers, Policy Modeling

JEL Codes: E24, J08, J64, R23

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1. Introduction

The Spanish labor market over the last few decades has been characterized by having generated exceptionally high unemployment rates when compared to those seen elsewhere in Europe (Bentolila and Jimeno, 2003; Jaumotte, 2011). The explanations as to the reasons behind such high and persistent levels of unemployment have been set out in many academic papers[1]. A further issue which has been the subject of much inquiry in the literature (Jimeno and Bentolila, 1998; Bande et al., 2008; Romero-Ávila and Usabiaga, 2008; Bande and Karanassou, 2013) is the enormous disparity between unemployment rates in the various regions in Spain and their persistence over time.

Given this backdrop, the present research pursues two objectives. Firstly, the spatial and temporal diversity of regional unemployment rates is used to split the latter into two components: on the one hand, the natural component of effective unemployment and on the other the cyclical component. To carry out this decomposition, the present work draws on multivariate techniques based on estimating stochastic frontiers. This methodology is applied to a database which provides information on the 17 autonomous communities in Spain for the period between 1982 and 2013[2]. A deeper understanding of the factors sparking the rate of effective unemployment and its evolution over the period considered is thus gained.

Having decomposed effective unemployment, the second objective is to compare our results to those obtained when using three univariate filters that are widely applied in economic literature: the Hodrick-Prescott filter (hereinafter, HP Filter), the Baxter-King filter (hereinafter, BK Filter), and the quadratic trend method (hereinafter, QT decomposition). The information to emerge from our results evidences major differences, particularly when conducting the comparison with the HP Filter and the QT decomposition. The proposal put forward in the present paper reduces the weight of the natural component of unemployment in favor of the cyclical, particularly during economic upturns. The results might have significant implications for economic policy in the sense that they could provide greater scope of action for policy-makers seeking to fight unemployment.

The remainder of the work is organized as follows. The first part of section 2 presents the conceptual framework underlying the decomposition of the effective rate of unemployment. The second part offers a review of the literature related to the decomposition of unemployment rates. Section 3 sets out the methodological aspects, both in terms of the stochastic frontier analysis used in the decomposition as well as the univariate filters employed in the subsequent comparison. Section 4 details the database used and provides a brief explanation of the variables applied in the study. Section 5 offers the main results obtained when decomposing unemployment through stochastic frontiers, comparing them with the decompositions obtained from the univariate filters and sets out certain economic policy implications. Finally, section 6 sums up the main conclusions to emerge from the work.

[1] The exceptional works of Blanchard and Wolfers (2000) and Blanchard (2006) highlight the role played by labor institutions when causing high unemployment rates in the face of adverse macroeconomic shocks. Another study which provides information on the topic under discussion is the work of Nickell et al. (2005).

[2] Spanish autonomous communities correspond to the second level (NUTS-2) of the Nomenclature of Territorial Units for statistics. For further information concerning the concept of NUTS, see: http://ec.europa.eu/eurostat/web/nuts/overview.

2. Conceptual framework and state of the art.

This section is divided into two parts. The first subsection details the conceptual framework based on which the decomposition of effective unemployment is carried out in the present research. The second subsection reviews the economic literature addressing the various techniques employed to determine the components of effective unemployment.

2.1. Conceptual framework

Economic theory states that there are different types of unemployment, so the unemployment rate might be decomposed according to distinct typologies. One popular classification, which may even be found in economy handbooks, draws a distinction between frictional, structural and cyclical unemployment[3]. In formal terms:

$$U_{it} = U_{it}^{F} + U_{it}^{ST} + U_{it}^{C} \tag{1}$$

where U_{it} is the effective rate of unemployment in region i at time t; U_{it}^{F} represents frictional unemployment; U_{it}^{ST} is structural unemployment and, finally, U_{it}^{C} reflects cyclical unemployment. It is often felt that frictional unemployment proves extremely hard to eliminate and that there will always be some unemployment of this kind. This component is explained based on the "job-search theory" and stems from the existence of asymmetrical or imperfect information amongst jobseekers and employers, which in turn means that "matching" in the labor market may take some time and that there will always be a certain level of unemployment[4].

Together with frictional unemployment, structural unemployment tends to be seen as a kind of unemployment linked to aggregate supply determinants (as opposed to cyclical unemployment, which tends to be linked to aggregate demand factors). This component appears to be due to imbalances between supply and demand in the job market which might lead to there being both unemployed people and unfilled job vacancies in firms at the same time[5]. In this sense, it should be stressed that macroeconomic literature has often considered that the sum of frictional unemployment and structural unemployment corresponds to a notion of equilibrium unemployment, referred to as Natural Rate of Unemployment or NRU[6]. In formal terms, this idea may be expressed through equation (2):

$$U_{it}^{NR} = U_{it}^{F} + U_{it}^{ST} \tag{2}$$

where U_{it}^{NR} refers to the natural rate of unemployment in region i at time t. Despite the many definitions of this component of unemployment (not all of them

[3] See Krugman et al. (2011), for instance.

[4] This theory was developed by Mortensen (1970) and McCall (1970). See Lippman and McCall (1976a; 1976b), Mortensen (1986) and Mortensen and Pissarides (1999) for a review of the topic. A recent example of this kind of literature may be found in the works of Tatsiramos and van Ours (2012, 2014).

[5] Such imbalances are due to institutional inflexibility, and are linked to downward wage rigidity (minimum wage or collective bargaining), unemployment benefits, job protection legislation, jobseeker efficiency when searching for work, labor market inflow and outflow, labor force skills, low labor productivity, the industry composition of unemployment or the demographic structure of the population, amongst other factors (Blanchard, 2017).

[6] The notion of equilibrium unemployment admits that even in the best cyclical conditions some unemployment would persist. Put in other words, there is never a market clearing situation in the neoclassical sense of the term.

compatible with each other), here it will be conceptualized as the medium (or long) term equilibrium unemployment rate (a view widely accepted)[7].

Clarifying even further, the notion of the natural rate of unemployment seeks to reflect the idea that, even when macroeconomic conditions are optimal and there is no problem concerning a lack of aggregate demand, there will always be "some" level of unemployment. The natural rate of unemployment should therefore be associated to aggregate supply determinants in macroeconomic models. Nevertheless, during a period of low economic growth or in a recession, resulting from an adverse demand shock[8], said aggregate demand would prove "insufficient" and cyclical unemployment would have to be added to the previously mentioned components. In other words, equation (1) might be re-written as:

$$U_{it} = U_{it}^{NR} + U_{it}^{C} \tag{3}$$

An extremely simplified way of illustrating this is through figure 1, which depicts a very simple labor market. The upward sloping curve L_{it}^{S} is the labor force, which grows since as the market wage increases (W_{it}) more people join, because their "static" reservation wage is being exceeded (recall the choice model between consumption and leisure). The N_{it}^{S} curve, which also displays a positive slope, reflects effective labor supply. The difference between L_{it}^{S} and N_{it}^{S} highlights the fact that not all active workers are immediately available for work. As the market wage increases, it exceeds the "dynamic" reservation wage (or that of the job-search theory) of a higher number of workers, with the latter more willing to accept the jobs they find. As a result, the distance between L_{it}^{S} and N_{it}^{S} is lower for higher salaries. Said horizontal difference between the two curves is the frictional unemployment (U_{it}^{F}).

Figure 1 also displays the labor demand curve under two scenarios related to aggregate production: expansion (y_0) and recession (y_1). It can be seen how even in a situation of equilibrium with production at a maximum, as in point A, coupled with a demand for work $L_{it}^{D}(y_0)$, unemployed workers would still exist as a result of frictional unemployment. In addition, the existence of a collective bargaining system, which strongly impacts on the mechanism for setting wages in the Spanish labor market, tends to establish a "collective bargaining" wage (W_{it}^{CB}) which is higher than the competitive wage (W_{it}^{PC}). This figure evidences how wage rigidity (due to institutional factors) gives rise to an excess of available labor, leading to an imbalance and sparking structural unemployment (U_{it}^{ST})[9]. As in the previous case, structural unemployment would exist even if there were a demand for labor such as $L_{it}^{D}(y_0)$, associated to a period of economic boom[10].

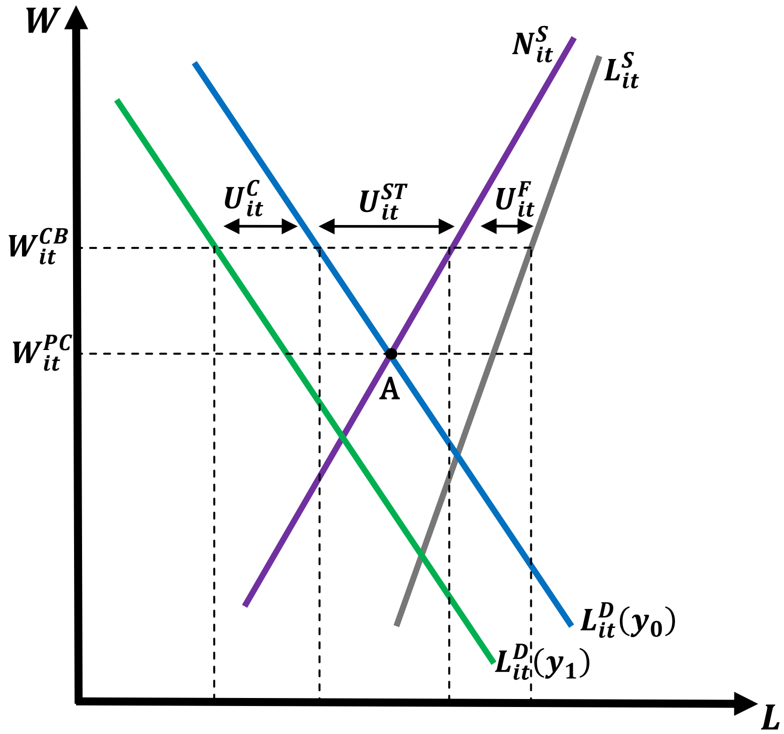
[7]The work of Rogerson (1997) offers several kinds of nomenclature for this term as well as varying definitions of the concept.

[8] Due, for example, to a fall in consumer confidence or business confidence. A contractive monetary policy or a cut in public spending might also account for insufficient aggregate demand, giving rise to a higher cyclical unemployment rate.

[9]Elhorst (2003) cites certain works that have studied the impact of collective wage bargaining on unemployment. In most cases, a positive effect emerges that would seem to confirm the previously posited hypothesis.

[10] A different type of structural unemployment would be that emerging from the disparities between the skills required for the job vacancies and those possessed by the unemployed workers. This kind of structural unemployment does not fit in a homogeneous labor market framework, as the one shown in figure 1. However, the basic idea that even in the best economic conditions there exist some structural unemployment remains.

Figure 1. Frictional, structural and cyclical unemployment



Source: Authors' own.

The works of Bentolila and Jimeno (2003), Simón et al. (2006) and Bande et al. (2008) provide empirical evidence concerning the influence of the collective bargaining system on the Spanish labor market. Due to the wage rigidity, such wages are prevented from playing their role as an equilibrium mechanism in the Spanish labor market[11]. Based on this, it may be stated that adjustment "via prices" fails to work correctly and that, as a result, adjustments mainly come about "via quantities" in the Spanish labor market[12].

The final element in equation (1) is so-called cyclical unemployment (U^C_{it}). This element refers to the reduction in labor demand sparked by a lack of aggregate demand which reduces companies' sales. Given that labor demand is a derived demand, a reduction in aggregate demand in the macroeconomic goods market leads labor demand to shrink. In figure 1, cyclical unemployment is reflected in the horizontal distance between curves $L^D_{it}(y_0)$ and $L^D_{it}(y_1)$. It should be stressed that this type of unemployment should be zero (from a strictly theoretical standpoint) when the economy is undergoing an "expansion" and, in contrast, is positive during periods of "recession" when labor demand shifts to the left, as can be seen in figure 1. As is well known, this type of unemployment can be corrected in the short term through expansive aggregate demand policies.

At this point, one important clarification should be made for the purposes of the present work between the notion of the Natural Rate of Unemployment or NRU, and the Non-Accelerating Inflation Rate of Unemployment, or NAIRU.

[11] For a more comprehensive explanation of the phenomenon, see Jimeno and Bentolila, (1998), Garcia-Mainar and Montuenga-Gomez (2003), Maza and Moral-Arce (2006), Maza and Villaverde (2009) or Bande et al. (2012).
[12]Cazes et al. (2013) show how, during the "Great Recession", in Spain, labor market adjustment was mainly carried out through the external margin of adjustment (redundancies and staff cutbacks) in the labor market.

Although the two concepts are frequently used indistinctly, there are several differences which call into question whether the NRU and the NAIRU are truly equivalent concepts. Following the work of Espinosa-Vega and Russell (1997), the two notions stem from quite differing schools of economic thought. Moreover, Tobin (1997) maintains that "the NAIRU and the NRU are not synonyms". The NAIRU is a relation at the macroeconomic level which, in a nutshell, relates observed unemployment to inflation. Should the effective unemployment rate exceeds the NAIRU, then the inflation rate ought to fall and vice versa. In contrast, following Grant (2002), the NRU is an equilibrium unemployment rate which is mainly determined by the institutional and demographic characteristics of the economy.

For the purposes of the present work, what is important is to realize that the concept of NAIRU is linked to a cyclical unemployment rate that could take negative values at certain periods (those in which the inflation rate rises). After all, a relatively simple estimation of the NAIRU is the intersection of an expectations-augmented Phillips curve with the "X" axis, with the effective unemployment rate being either higher or lower than said value. This would be equivalent to stating that the sum of frictional and structural unemployment is greater than effective unemployment during periods of increasing inflation. The notion of NAIRU proves extremely useful in order to understand inflationary pressures in macroeconomic models. Nevertheless, claiming that the sum of frictional and structural unemployment might exceed effective unemployment is somewhat strange for labor economy models, which have a more microeconomic foundation and consider effective unemployment to be the sum of the three components that make up equation (1), in which none of them can be negative (in other words, $U_{it}^{F} \geq 0$; $U_{it}^{ST} \geq 0$; $U_{it}^{C} \geq 0$).

In the present work, we are more interested in the concept of NRU than NAIRU. Although we analyze labor markets from a macroeconomic standpoint, inflation has no major bearing here. Nevertheless, we are very interested in measuring which part of unemployment remains even when aggregate demand is at its highest level and there is consequently no lack of aggregate demand. This has important consequences from the standpoint of economic policy, since it would allow us to pinpoint, within the effective unemployment rate of each territorial unit and at each point in time, how many unemployment rate points are attributable to aggregate supply factors and how many to aggregate demand factors. With this aim in mind, we apply the stochastic frontier technique and estimate a composed-error econometric model. In this regard, we draw partially on the proposal of Hofler and Murphy (1989) and more recently Aysun et al. (2014), works we will refer to later. In the present work, we rationalize the NRU as a notion of medium (or long) term equilibrium unemployment, dependent on factors which the literature has considered determinants of frictional and structural unemployment, which we denote as the vector of variables X_{it}. In our view, the natural minimum or "efficient" unemployment would therefore be a function of said vector of variables, $U_{it}^{NR} = f(X_{it})$.

Deviations from said minimum would be deemed inefficient and would result from insufficiencies in aggregate demand, in other words cyclical unemployment is modeled as a non-negative disturbance $U_{it}^{C} = u_{it} \geq 0$. Finally, assuming linearity, $f(X_{it}) = X_{it}\beta$, the "econometric" version of (1) would be:

$$U_{it} = X_{it}\beta + v_{it} + u_{it} \quad (4)$$

where v_{it} is a random conventional disturbance. Equation (4) implicitly assumes that cyclical unemployment has a minimum value equal to 0. Otherwise, situations could emerge in which the natural rate of unemployment was higher than actual effective unemployment, as already pointed out[13]. In other words, the U_{it}^{NR} component acts as a limit or lower boundary for effective unemployment ($U_{it} \geq U_{it}^{NR}$).

2.2. State of the art

Decomposing the unemployment rate into its different types is a recurring theme in economic literature, for which a range of different methods have been used[14]. One common option when obtaining the components of effective unemployment is to use univariate statistical filters to split the unemployment rate into various elements. Two of the most widely used filters are undoubtedly the HP Filter (Hodrick and Prescott, 1997) and the BK Filter (Baxter and King, 1999). These filters are usually accompanied by decomposition through the QT decomposition, most probably due to the simplicity of its application.

The HP Filter has often been used when estimating "Okun's Law" in an effort to extract the natural component and the cyclical component from effective unemployment (Apergis and Rezitis, 2003; Perman and Tavera, 2005; Adanu, 2005; Villaverde and Maza, 2007 and 2009; Ball et al. 2013). The QT decomposition has also been widely used in economic literature related to "Okun's Law", most likely because it offers very similar results to the HP Filter (Adanu, 2005; Villaverde and Maza, 2007 and 2009). Finally, there are also various studies in which the BK Filter has been used in the same context as the two previous ones (Freeman, 2000; Apergis and Rezitis, 2003; Villaverde and Maza, 2009). The economic literature has also drawn on another set of "more complex" econometric techniques in an attempt to obtain the various components of effective unemployment. Prominent amongst these are the models based on the "Phillips curve" to estimate the natural component of effective unemployment (Blomqvist, 1988; Hahn, 1996; Apergis, 2005), techniques based on the Kalman Filter (Moosa, 1997; Mocan, 1999; Salemi, 1999), or estimations based on structural autoregressive vectors (SVAR) (King and Morley, 2007).

However, few studies have been found which use the econometric approach of stochastic frontiers to decompose the effective rate of unemployment. One of the pioneering works in this sense is Warren (1991) which uses frontier estimation to obtain the frictional component of the unemployment rate. Warren (1991) takes matching models in the labor market as a starting point. With this background, he applies an approach based on a model of employment growth when the economy is in steady state to derive the expression of the unemployment rate in the steady state[15]. At a second stage, and by applying an OLS model, Warren obtains the mean unemployment rate for the US manufacturing sector between April 1969 and

[13] In the microeconomic literature addressing stochastic cost frontiers (see for example Revoredo-Giha et al., 2009; Sav, 2012 or Duncan et al., 2012), the "frontier cost" is the minimum possible and can never exceed the observed cost. Hofler and Murphy (1989) and Aysun et al. (2014) extrapolate this idea to the labor market to decompose the unemployment rate. We modify this interpretation slightly and apply it to the Spanish labor market.
[14] The work of Bean (1994) provides a comprehensive review of the topic in hand.
[15] It is precisely the use of information concerning vacancies which means that in the present work we are unable to apply Warren's approach (1991). It is a well known fact that information concerning vacancies in Spain is extremely poor.

December 1979. A stochastic frontier of production is subsequently applied to determine frictional unemployment in the manufacturing sector. Finally, by subtracting both estimated rates a measure of inefficiency for said labor market is derived.

Another study carried out along the same line is that of Bodman (1999) who takes the theoretical model set out in Warren (1991) as a starting point. The main differences emerge from the regional perspective (the analysis is carried out for all the states in Australia) and from how the inefficiency term of the error is modeled, which is estimated following the proposal of Battese and Coelli (1995). Having obtained frictional unemployment and the inefficiency of the error term, Bodman finds a positive effect on the inefficiency of Labor Party administration in most of the states analyzed.

One study more closely aligned to the approach adopted in the present research is that of Hofler and Murphy (1989). These authors draw on a database of unemployment rates containing both transversal and temporal information for the US, considering that there is a lower-envelope function which the authors link to the notion of frictional unemployment rate. They model frictional unemployment using deterministic components such as the stochastic cost frontier (a lower frontier), and the distance from that lower frontier to effective unemployment which they term "excess supply unemployment" in the labor market[16]. At a second stage, they find that it is the variables related to social transfers, the size of the youth labor force, female participation rates, educational attainment and net migration rate, which account for both the level of frictional unemployment in each state as well as the changes to occur between 1960 and 1979.

Finally, in the research carried out by Aysun et al. (2014) elements from the three previous studies are combined, using the modeling of one upper and one lower stochastic frontier to decompose the unemployment rate into its various components. One the one hand, they use a model and a method which are similar to that used in Warren (1991) to extract the frictional component of unemployment. They also apply a cost stochastic frontier to ascertain the structural component of the unemployment rate as was done in Hofler and Murphy (1989), using a specification of the expectations-augmented Phillips curve. The authors thus obtain a measure of structural unemployment which is always lower than the effective **component.**

3. Methodology

This section is also divided into two parts. In the first, a brief explanation is given of the stochastic frontier technique used to decompose unemployment. In the second, a description is provided of the univariate filters employed to accomplish the work's second objective.

[16] The model put forward in Hofler and Murphy (1989) to illustrate frictional unemployment corresponds to the following equation: $U_{tj} = \underbrace{\beta_0 + \beta_1 t + \beta_2 t^2 + w_{tj}}_{F_{tj}} + \vartheta_{tj}$. where U_{tj} refers to the unemployment rate during period t and state j, F_{tj} encompasses the components of frictional unemployment and ϑ_{tj} reflects excess supply. The stochastic cost frontier approach is used to separate w_{tj} from ϑ_{tj} and to find the lower frontier which corresponds to the frictional component of unemployment.

3.1. Stochastic frontier analysis

The decomposition presented in the conceptual framework is based on the assumption that all the components are positive. As a result, the natural rate of unemployment constitutes a minimum value below which effective unemployment cannot fall, and any deviation from this minimum is considered inefficiency that can be corrected by applying aggregate demand policies. As already pointed out in subsection 2.1, this is a composed-error model which can be estimated using stochastic frontiers. The first econometric models to introduce this technique are to be found in the seminal papers of Aigner et al. (1977) and Meeusen and van Den Broeck (1977)[17]. In its costs version, this estimation technique allows a minimum value which is situated below the observed dependent variable to be identified.

As already pointed out, the ultimate goal is to separate the effective rate of unemployment (U_{it}) into two components: the natural unemployment (U_{it}^{NR}) and the cyclical unemployment (U_{it}^{C})[18]. However, in order to identify the two components, the starting point is to specify the natural unemployment as shown in equation (5):

$$U_{it}^{NR} = \beta_1 X_{it} + v_{it} \tag{5}$$

where X_{it} is a vector of explanatory variables, β_1 is the vector of coefficients to be estimated and v_{it} is a statistical noise deemed symmetrically and independently distributed as a $N(0, \sigma_v^2)$. This natural component constitutes a lower envelope or cost frontier below which the effective unemployment rate will never fall. However, the natural unemployment formulated econometrically in equation (5) is not observed directly. The available information corresponds to the effective unemployment rate which is greater than or equal to the natural ($U_{it} \geq U_{it}^{NR}$). The effective rate of unemployment may thus be represented as the sum of U_{it}^{NR} and a non-negative random disturbance identified with cyclical unemployment (U_{it}^{C}), through the following mathematical expression:

$$U_{it} = U_{it}^{NR} + u_{it} \tag{6}$$

where: $u_{it} = U_{it}^{C}$ and u_{it} is an error term which is expected to be positive and independently distributed. It should again be stressed that this term will always take a positive value or one equal to 0 in the best of cases (Aysun et al. 2014). Finally, by grouping equations (5) and (6), we obtain expression (7) which coincides with equation (4) presented in the theoretical framework:

$$U_{it} = \beta_1 X_{it} + \varepsilon_{it} \tag{7}$$

where: $\varepsilon_{it} = v_{it} + u_{it}$

Taking account of the final specification of equation (7), a maximum likelihood estimation would need to be applied given the presence of a composed error econometric model. This type of estimation allows us to obtain the two error components separately and to calculate the variance of each. It is thus possible to

[17] Kumbhakar and Lovell (2003) and Greene (2008) provide a highly detailed exposition of this type of econometric technique.

[18] As highlighted previously, the lack of sufficiently extensive and time-comparable information concerning existing vacancies in the labor market makes it extremely difficult to extract the frictional component (U_{it}^{F}) using the econometric techniques observed in some of the works referred to in the literature review. As a result, said component will be estimated together with the structural component of unemployment.

apply a statistical test to determine the existence of the frontier and whether it is a production or a cost frontier. As it will be shown, in our case, a lower stochastic frontier (cost frontier) is estimated which, according to our approach, coincides with the natural unemployment (U_{it}^{NR}) and implies a lower limit for U_{it}.

Nevertheless, in order to estimate u_{it}, which is here identified with U_{it}^{C}, it is necessary to establish a distribution for the two error components of ε_{it} (Jondrow et al., 1982). In the case of the v_{it} component, there would appear to be no problem since there seems to be a strong consensus in the empirical literature that said component is distributed in the form $N(0, \sigma_v^2)$, as we state before. The main problem emerges when it is needed to consider the distribution of the u_{it} term. Here, several distributions are proposed in the econometric literature: Normal Truncated (Stevenson, 1980), Semi-Normal (Aigner et al., 1977), Exponential (Meeusen and van Den Broeck, 1977) and Gamma (Greene, 1990). For the present study, and as occurs in the works of Hofler and Murphy (1989) and Aysun et al. (2014), Semi-Normal distribution is chosen for this error component.

3.2. Univariate filters

In order to put our proposed decomposition into perspective it is useful to compare it to other alternative methods used in the literature. To achieve this, three univariate filters are used which also allow effective unemployment to be decomposed, the HP Filter, the QT decomposition, and finally, the BK Filter[19]. These filters have been widely used when analyzing time series and enable any time series (Z_t) to be broken down into its two components: the trend (T_t) and the cycle (C_t).

At this point, it should be stressed that several of the studies cited previously in this text and which use these filters link the trend component to the concept of the NRU and the NAIRU, and make no "clear" distinction between the two (Perman and Tavera, 2005; Adanu, 2005; Villaverde and Maza, 2007 and 2009; Ball et al. 2013). In a similar line, the work of Blanchard and Katz (1997) defines the natural rate of unemployment as follows: "The natural rate of unemployment is typically interpreted as the rate of unemployment consistent with constant (non-accelerating) inflation", referring to the context of the "Phillips Curve" and establishing no differences between NRU and NAIRU. Based on this, we are able to compare our estimations of the NRU with those obtained using the HP Filter, with the QT decomposition or with the BK Filter. This comparison is also carried out for the cyclical component.

Applying these filters to our effective unemployment series at a regional scale yields the following equations:

$$U_{it} = U_{it}^{HPT} + U_{it}^{HPC} \tag{8.1}$$

$$U_{it} = U_{it}^{QTT} + U_{it}^{QTC} \tag{8.2}$$

[19] See Hodrick and Prescott (1997) for a more detailed explanation of the HP Filter. For a more extended definition of the BK Filter, see Baxter and King (1999) and Pizarro (2001). The QT decomposition is a purely deterministic procedure, the aim being to model the element to be decomposed through a quadratic trend process: $Z_{it} = \delta_0 + \delta_1 T + \delta_2 T^2 + \omega_{i,t}$ In this case, Z_{it} is the variable to be decomposed, δ_0 is the constant term of the equation, T and T^2 are the components of the quadratic trend, and finally $\omega_{i,t}$ is the error term. However, in the literature using QT decomposition, this latter term would, in turn, reflect the cyclical component of the variable we aim to decompose.

$$U_{it} = U_{it}^{BKT} + U_{it}^{BKC} \quad (8.3)$$

where U_{it} is the effective unemployment in region i at time t; U_{it}^{HPT}, U_{it}^{QTT} and U_{it}^{BKT} refer to the trend component of the effective unemployment obtained through the HP Filter, the QT decomposition, and the BK Filter, respectively, for each region i at time t. Finally, U_{it}^{HPC}, U_{it}^{QTC} and U_{it}^{BKC} refer to the cyclical components obtained through each filter for region i in year t.

4. Database

The data used in the present study were obtained from the Spanish Labor Force Survey (Encuesta de Población Activa, EPA) published by the National Statistics Institute (Instituto Nacional de Estadística, INE) and the Valencian Institute of Economic Research (Instituto Valenciano de Investigaciones Económicas, IVIE). All the variables used have an annual frequency for the period between 1982 and 2013 and are disaggregated for the 17 Spanish autonomous communities[20]. A summary of the variables used in this study, how they have been defined and their source may be found in table A1 in the Appendix.

The first part of the empirical analysis involves decomposing the regional unemployment rate. As a result, this is the dependent variable and the central one in our empirical work. In order to carry out the decomposition, different explanatory variables which might affect the evolution of the unemployment rate are used. The two first explanatory variables contained in table A1 in the Appendix have a demographic component. The first of these is the female activity rate and reflects the impact of women's labor participation in the effective rate of unemployment[21]. According to Elhorst (2003), the influence of this variable on the unemployment rate gives rise to diverse results. The second of the explanatory variables is the percentage represented by the population of 16 to 24 year-olds with regard to the total in each autonomous community. This variable is included as there is empirical evidence of a positive correlation between the weight of the youth population and the unemployment rate (Johnson and Kneebone, 1991; Murphy and Payne, 2003). This might be due to the fact that the young, as a result of their limited work experience, are less skilled when it comes to finding jobs than their older counterparts. Their having less specific human capital might also prove to be a determining factor when accounting for high youth unemployment rates. Based on this, younger people tend to suffer longer periods out of work[22].

The second group of regressors is made up of a series of variables reflecting the industry composition of regional employment. The extant literature would seem to point to one of the causes of the differing unemployment rates at a regional scale being the industry composition of labor in each region[23]. Differences in wages, job skills or competitiveness are key factors influencing the impact which the industry composition has on unemployment levels[24]. In a context where the Spanish regions evidence substantial differences in terms of industry composition,

[20] The autonomous cities of Ceuta and Melilla have been excluded from the research due to the scant representativeness of some of the variables used.
[21] Lázaro et al. (2000), Azmat et al. (2006) and Bertola et al. (2007) point to some of the driving factors behind the recurring female unemployment rates.
[22] In Maguire et al. (2013), some references explaining the reasons underlying the high rates of unemployment amongst youngsters in Spain (16-24 year olds) over the period 2007-2013 may be found.
[23] See Elhorst (2003).
[24] See Summers et al. (1986).

this is expected to be a determining factor underlying regional differences in unemployment rates.

Table A2 in the Appendix shows some descriptive statistics of the variables referred to earlier which reflect the interregional differences between them. The unemployment rate, as a central variable in the analysis, evidences a high regional variability, ranging from 25.87% in Andalusia or 23.75% in Extremadura, to 11.27% in Navarre, 11.65% in La Rioja or 12.06% in Aragon. These differences are also apparent in the other variables used. The ones found in the female participation rate are particularly important. There are regions such as the Balearic Islands or Catalonia with levels of female participation rate around 45%, whilst in Extremadura or Castilla-La Mancha less than 35% of women who are of working age form part of the labor force. The weight of the young population is less disparate amongst the various regions, despite which it can be seen that the region displaying the greatest weight of 16 to 24 year-olds is the Canary Islands (18,74%), whilst Asturias is at the other extreme with less than 14% of working age population being made up of youngsters.

The variables measuring the industry composition also evidence the different productive structure in each region. The most extreme values are perhaps to be found in agriculture which varies between over 22% employed in Galicia and 1% in the Community of Madrid. In the case of manufacturing, the extremes are marked by La Rioja with over 27% employed compared to fewer than 7% in the Canary Islands. Finally, the service sector is particularly important in the two archipelagos and in the Community of Madrid with over 70% employed whereas in La Rioja or Galicia this figure is around 50%.

5. Results

As with the previous sections, this one will also be divided into several parts. The first part involves the decomposition of the effective rate of unemployment into the natural unemployment (U_{it}^{NR}) and the cyclical unemployment (U_{it}^{C}) through the use of stochastic frontiers. In the second part, a comparison is drawn between the previously performed estimations and those obtained using the HP Filter, the BK Filter and the QT decomposition. Finally, the implications for economic policy of the results obtained are set out in the third part.

5.1. Decomposition of effective unemployment

Having introduced the stochastic frontier technique as a decomposition mechanism for effective unemployment, the results corresponding to the estimation are now presented. This is where the present work differs slightly from the proposal put forward by Hofler and Murphy (1989), since we opt for a more comprehensive parameterization of the frontier[25]. Two different econometric specifications have been used in the estimates carried out. Expressions (9) and (10) are the specific versions of the general equation (7). In both cases, as control covariates we include demographic features (percentage of youth population and female participation rate), industry composition (percentage of people employed in agriculture,

[25] This greater parameterization of the frontier relates to an interest in capturing some important determinant factors of the NRU. It has to be taken into account that the Hofler and Murphy (1989) approach considers only the frictional unemployment to be part of the frontier, whereas in our proposal the frontier is made up of both the frictional and the structural unemployment.

manufacturing and services) together with a dichotomous variable ($D2001$) which takes the value 1 after 2001 and 0 in the previous years[26].

Expression (10) adds, with regard to equation (9), a lineal trend (T) to the previous control covariates. It should also be pointed out that fixed regional effects have been used in all the specifications to reflect unobservable heterogeneity at a territorial scale (μ_i).

$$U_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 D2001 + v_{it} + \mu_i + u_{it} \qquad (9)$$

$$U_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 D2001 + \beta_3 T + v_{it} + \mu_i + u_{it} \qquad (10)$$

Table A3 in the Appendix shows the results obtained for the two specifications applied. Broadly speaking, it can be seen a great similarity between the coefficients obtained regardless of whether or not the temporal trend is included. It can also be seen that in both cases, it can be accepted that there is a cost frontier at a 5% level of statistical significance.

A close look at the variables used when modeling the frontier yields the following conclusions. The female activity rate has a positive and significant effect on NRU at a regional scale, an effect reinforced when a trend is included in the model. This result seems to indicate that the gradual incorporation of women into the labor market since the early 1980s has led to an increase in regional NRUs, due mainly to the fact that female unemployment rates are higher than those of men. With regard to the second demographic variable, a positive and significant effect of the percentage of young people on regional NRUs can also be seen. This effect is common to both specifications and has a greater coefficient than that of the female activity rate is found[27]. These results are consistent with the hypotheses formulated earlier concerning the youth population and reflect the importance of youth unemployment when determining aggregate unemployment levels[28].

The second group of control covariates included in the model concern the industry composition. As with the previous case, all display a positive and highly significant effect in both specifications, reflecting the fact that, ceteris paribus, all the sectors evidence a higher natural rate of unemployment than the one used as a reference. Given that the variable excluded is the percentage of workers in the construction industry, it may be concluded that the remaining sectors display higher levels of unemployment and that it is the percentage of workers in the service sector which is the most relevant variable when explaining unemployment levels.

It can also be seen how manufacturing and construction are the industries which have had the least impact on the dependent variable. One tentative explanation to account for these results might be found in the great weight which low-skilled jobs have in the service sector. In agreement with the literature, times of crisis cause long periods of unemployment amongst low-skilled workers, which

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[26] This dummy variable is introduced due to the fact that in 2001 methodological changes were made which affect how unemployment is measured. The methodological changes made may be seen at http://www.ine.es/epa02/meto2002.htm.

[27] López-Bazo et al. (2005) also report a positive effect of the percentage of the youth population (16-25) on unemployment, and establish that said variable contributes significantly to explaining regional disparities in unemployment.

[28] Dolado et al. (1999 and 2000) and Dolado et al. (2002) show some of the causes and consequences of the "inefficient" functioning of the labor market for young people in Spain.

increases their own rate of structural unemployment[29]. If we add to this the fact that in the service sector there is high job turnover and that in many instances firms offer little or no training[30], we are left with a low-skilled workforce with low employability. As for the dichotomous variable reflecting the methodological change in how unemployment is measured after 2001, it has a negative and highly significant effect on both specifications.

This result indicates that the new methodology adopted by the INE contributes towards lowering the effective rate of unemployment. Finally, the linear trend included in specification 2 does not prove to be significant. Based on these estimates, predictions are made regarding the values of the frontier and inefficiency. It is thus possible to obtain the decomposition of the effective unemployment rate in the components previously referred to: U_{it}^{NR} and U_{it}^{C}.

Figure 2 shows the evolution of the NRU (U_{it}^{NR}) for all the autonomous communities[31]. The mean value of this component throughout the whole period is 12.94 percentage points. Above the mean, we find certain extreme values such as Andalusia (23.23), Extremadura (20.22) and the Canary Islands (17.26). The regions which evidence a lower U_{it}^{NR} value are Navarre (8.32), La Rioja (8.45) and the Balearic Islands (8.87)[32]. A different set of insights comes from the relative values, i.e. the importance of U_{it}^{NR} when explaining overall levels of effective unemployment.

It is once again the regions displaying the highest levels of NRU which account for the greatest percentage of effective unemployment. Specifically, this component explains 89.78% of unemployment in Andalusia, 85.16% in Extremadura and 83.21% in the Canary Islands. In the case of the regions in which the U_{it}^{NR} has less weight on effective unemployment, these are again the regions which evidence the lower levels of absolute unemployment: specifically, the Balearic Islands (70.24%), La Rioja (72.57%) and Navarre (73.83%), although Aragon with a rate of 73.80% joins the list.

Finally, it is worth reflecting briefly on the similarity in the profile displayed by the evolution of this component of unemployment in all the autonomous communities. Said similarity is less clear at the start of the period but becomes more intense after the mid 90s, displaying a noticeable "U" shape. Specifically, there is a sharp drop until the mid 2000s followed by a marked increase coinciding with the "Great Recession".

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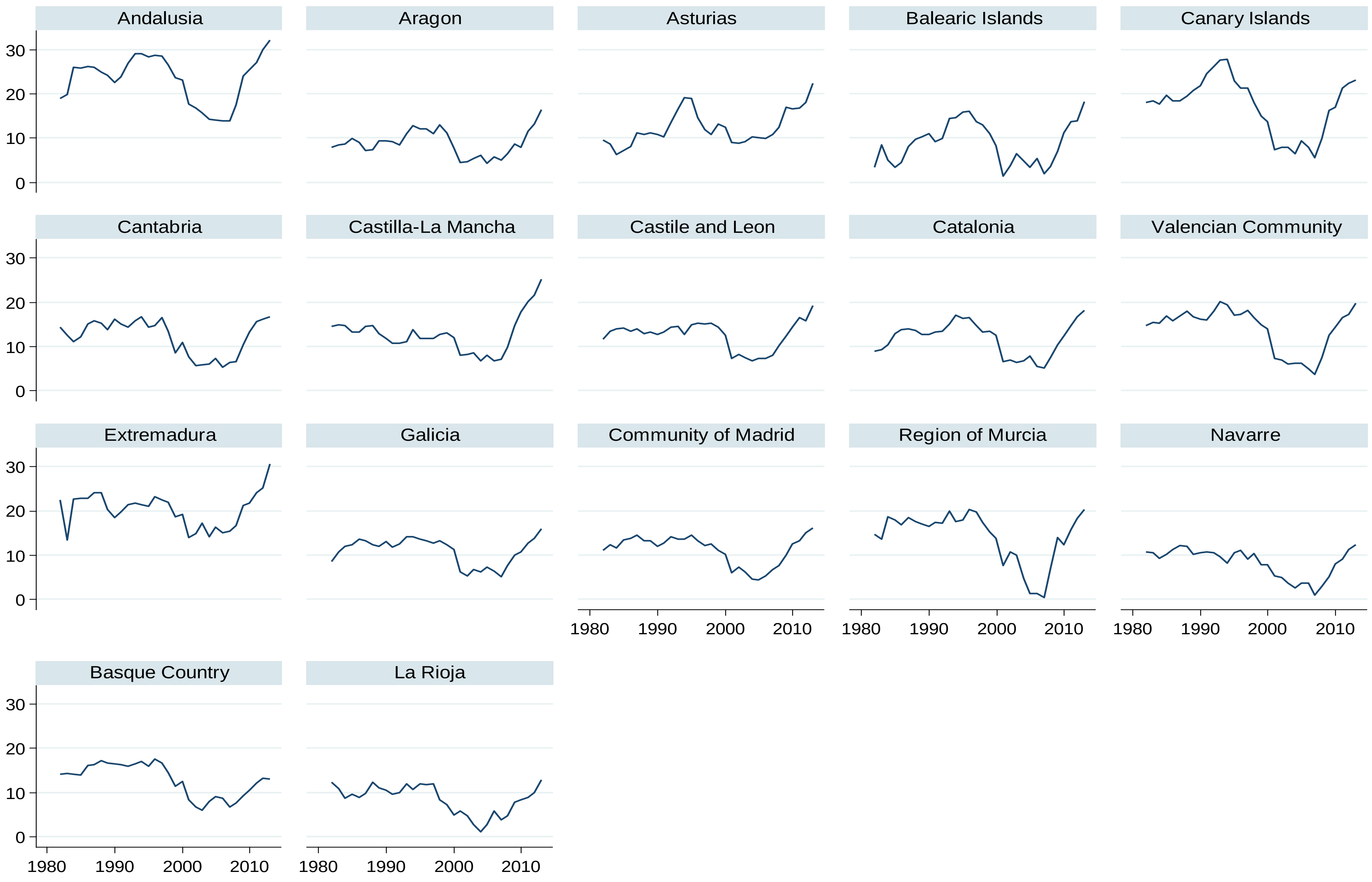
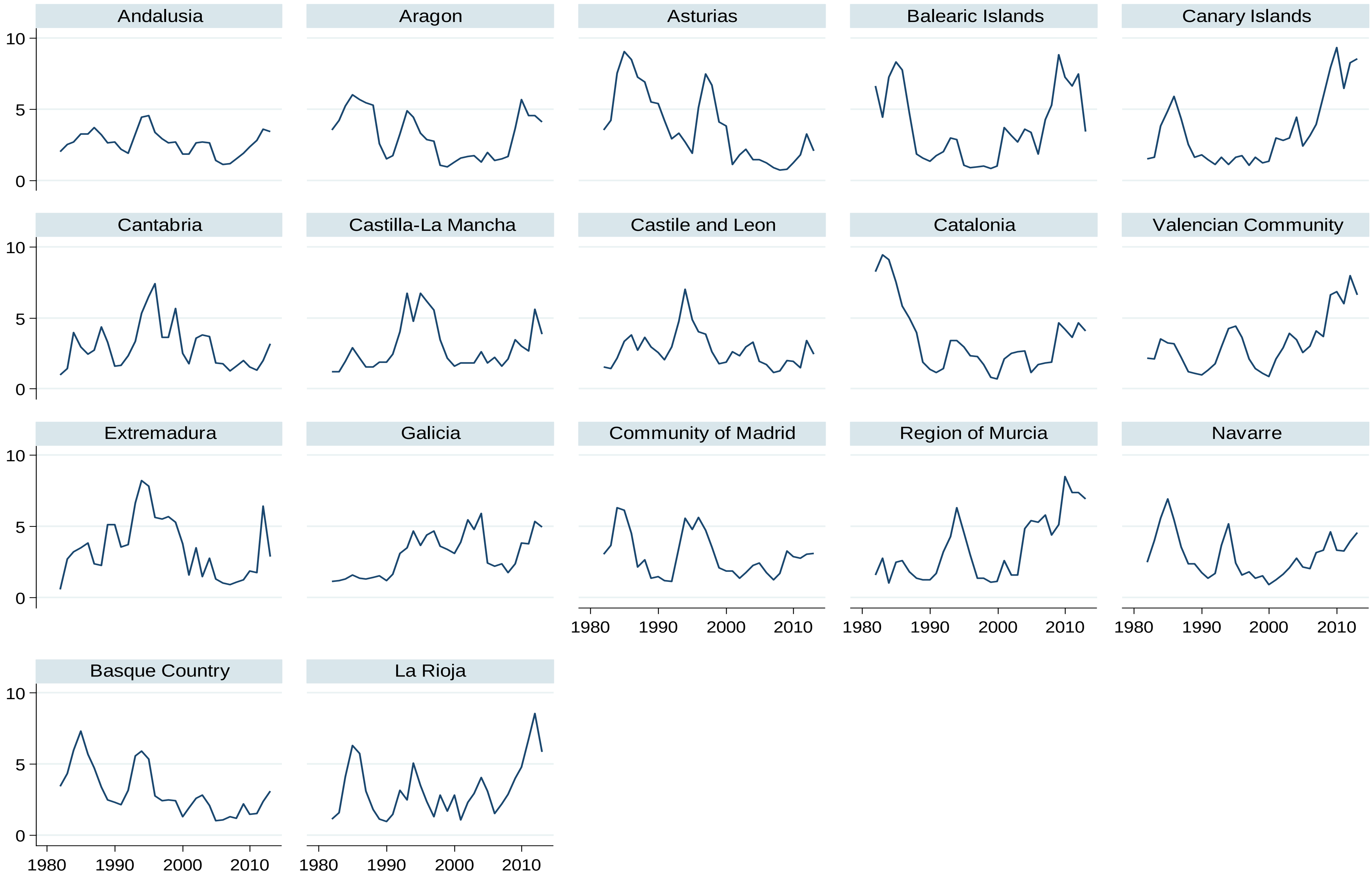
[29] Using a panel that includes 21 OECD countries, Oesch (2010) offers empirical evidence concerning which variables most impact on low-skilled worker unemployment rates.
[30] A good example for the case of Spain might be certain jobs in the tourist industry.
[31] Estimates have been performed based on specification 1. We have also carried out a similar analysis using specification 2, giving very similar results, with a correlation coefficient between the two specifications equal to 0.9998. It is worth mentioning that we also conducted econometric specifications that only included industry variables, again yielding very similar results. These results are available upon request from the authors.
[32] Detailed results are available to those interested upon request from the authors.

Figure 2. Natural unemployment (U_{it}^{NR}) by autonomous community (1982-2013)



Source: Authors' own.

Figure 3. Cyclical unemployment (U_{it}^{C}) by autonomous community (1982-2013)



Source: Authors' own.

Figure 3 shows the cyclical unemployment (U_{it}^{C}) at a regional scale[33]. In aggregate terms, the mean value for this component is 3.19 percentage points, which represents one quarter of NRU. The regions which most exceed this value are the Balearic Islands (3.76), Asturias (3.74) and Extremadura (3.52), although the Canary Islands, Catalonia, the Valencian Community and the Region of Murcia are also above the mean. In contrast, the regions showing the lowest component of cyclical unemployment are Andalusia (2.64), Castile and Leon (2.76) and Castilla-La Mancha (2.94)[34]. In this second case, no comments need to be made concerning the relative importance of this component on the effective unemployment rate since both components are complementary and therefore, where natural unemployment displays a greater weight, cyclical displays less, and vice versa. With regard to the time evolution of this component in all the autonomous communities, certain similarities among them are also in evidence, with a slight final peak coinciding with the period linked to the "Great Recession".

5.2. Comparison with filter decomposition

In this section, the results of the natural unemployment (U_{it}^{NR}) and cyclical unemployment (U_{it}^{C}) obtained by means of the decomposition of stochastic frontiers are compared to those obtained using the univariate filters defined previously[35]. Figures 4 and 5 show the estimations of each component of effective unemployment using the filters and the stochastic frontier approach (hereinafter, SF estimations). Figure 4 shows how the HP Filter, the QT decomposition and the BK Filter lead to a "mean overestimation" of the natural unemployment when compared to the SF estimations obtained in this study. This result is supported by the descriptive statistics of the natural unemployment in table A4 in the Appendix. The data show how the mean value of NRU for the SF estimations is lower than those of the HP Filter, the QT decomposition and the BK Filter for all the autonomous communities.

Figure 4 also shows how the estimations obtained using the HP Filter and QT decomposition bear a close resemblance throughout the whole of the study period. Nevertheless, those obtained using the BK Filter vary to a greater extent than the two previous ones and resemble the SF estimations more. This result is also in evidence when observing the data corresponding to the standard deviation shown in table 4 of the Appendix. These deviations are greater in the case of the SF estimations and the BK Filter estimations, which also display greater cyclical behavior.

Based on what can be observed in figure 4, four different periods emerge with regard to the SF estimations and their comparison to the three other methods. The first period is seen to commence in 1982 and conclude in 1993, approximately. During this period, the SF estimations for the NRU evidence lower mean values than those of the univariate filters in all the autonomous communities. The second

[33] The estimates of the cyclical component have also been performed with specification 1. The estimates obtained using specification 2 are very similar, with a correlation coefficient between the two specifications equal to 0.9993. Again, we also conducted econometric specifications that only included industry, yielding very similar results. These results are available upon request from the authors.

[34] Detailed results are available upon request from the authors.

[35] Following the recommendations of Ravn and Uhlig (2002), we have established a value equal to 1600 for the "λ" parameter, with regard to the HP Filter. In the case of the BK Filter, the following values have been established in line with the recommendations of Pizarro (2001): 2 for high frequencies, 8 for low frequencies and 3 for the number of lags to be used.

period commences in 1994 and finishes in 1998, approximately. During this period, the SF estimations display a greater similarity to those obtained using the HP Filter and the QT decomposition. The third period commences in the late 1990s (1999) and concludes near the end of the first decade of the 21st century (2010). The salient feature of this period is that the SF estimations again evidence significantly lower mean values than those of the remaining filters, particularly for the case of the HP Filter and the QT decomposition. Finally, the last period covers the latter years of the sample (2011-2013). Over this small period, the estimations obtained using the HP Filter and the QT decomposition and their mean values are again very similar to the estimations for most of the autonomous communities. In the case of the BK Filter no values are obtained for this period. This is so because the BK Filter implies the loss of a certain number of observations at the beginning and at the end of the period studied. Table A4 in the Appendix also shows the mean and the deviation of the estimation performed for NRU during each of the sub-periods and for each econometric technique. The data collected there give support to what we have pointed out concerning figure 4.

Figure 5 represents the cyclical unemployment estimated using the various methods. In this case, the HP Filter, the QT decomposition and the BK Filter provide an estimation of the cyclical unemployment which is generally "underestimated" when compared to the SF estimations. It can also be seen how the estimations obtained by means of the HP Filter and the QT decomposition are very similar and that the value of cyclical unemployment given by the BK Filter resembles the SF estimations more closely. The figures contained in table A5 in the Appendix give support to these results. It can be seen how the mean value estimated by the HP Filter, the QT decomposition and the BK Filter is significantly lower than that of the SF estimations for all the regions. The figures in table A5 also reveal how the SF estimations evidence a similar standard deviation to the BK Filter estimations and which is lower than that offered by the HP Filter and the QT decomposition estimations.

Let us say some words on the four periods mentioned before, but now regarding the cyclical unemployment. During the first period, the SF estimations are similar to those obtained using the univariate filters, although the mean values are noticeably higher for all the autonomous communities. During the second period, as occurred with the natural unemployment, the SF estimations of the cyclical unemployment display similar mean values to those of the univariate filters in general terms. Nevertheless, it can be observed lower values than those of the HP Filter and the QT decomposition in several autonomous communities, and higher values than those of the BK Filter in most cases. During the third period, the SF estimations are clearly higher than those obtained with the HP Filter and the QT decomposition, which tend to evidence negative mean values for cyclical unemployment. In this case, the SF estimations of the cyclical unemployment are also higher than those of the BK Filter although these are not as negative as those of the two other filters. For the last period, we only have estimations for the HP Filter and the QT decomposition (as mentioned earlier, it is not possible to obtain estimations for the BK Filter due to the technique used to calculate it). In this case, the estimations of the HP Filter and the QT decomposition and their mean values are above most of the SF estimations[36]. All of these results set out in detail in the

[36] In the case of the Balearic Islands, the Valencian Community and La Rioja the values of the "SF estimations" are slightly higher than those estimations of the HP Filter and the QT decomposition, particularly for 2011 and 2012.

previous paragraphs, and which can be observed in figure 5, are once supported by the data contained in table A5 in the Appendix for each of the sub-periods studied.

5.3. Economic policy implications

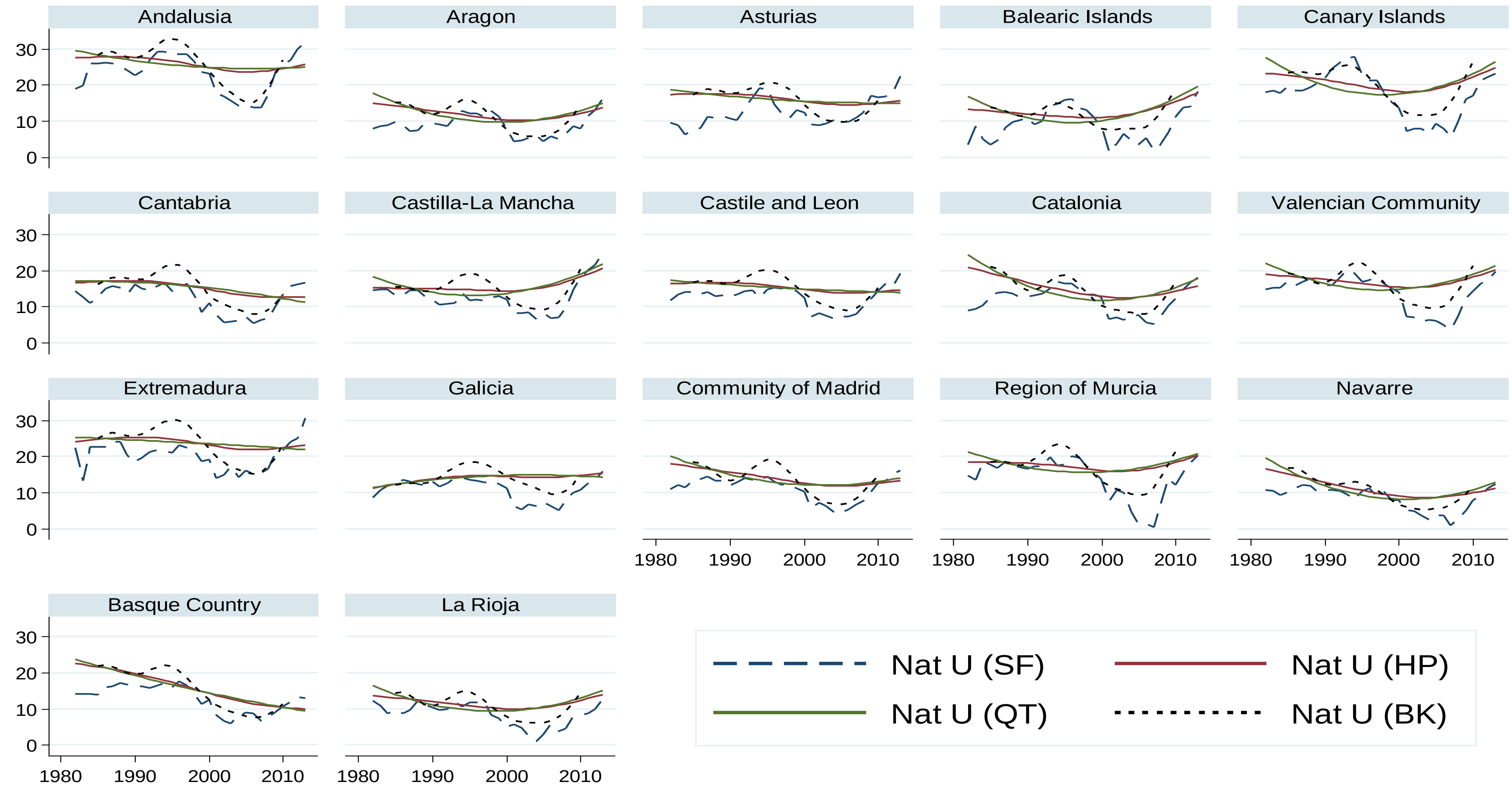
In our view, the SF estimations of NRU and, consequently, of the cyclical unemployment are quite appealing from an economic policy viewpoint. From our econometric work four key features that might be useful for economic policy outcomes can be drawn.

Firstly, in the previous sections it has been shown up that when estimating the natural unemployment (U_{it}^{NR}) and the cyclical unemployment (U_{it}^{C}) differences emerge depending on which method is used. The HP Filter, the QT decomposition and the BK Filter, are univariate filters based on the use of the past values of the variable to be decomposed. These filters are based on purely statistical criteria and therefore lack any theoretical economic foundation when estimating the various components of observed unemployment (Gómez and Usabiaga, 2001).This leads to a lack of interaction with the economic variables which might influence each component. A further issue to arise when positing the use of these filters is that the results are sensitive to the choice of the statistical parameters required to carry them out. In this way, different estimations may be obtained depending on the choice made by the researcher concerning these parameters (Fabiani and Mestre, 2000). The SF estimations incorporate multivariate information based on economic theory. Such methodological differences mean that the SF estimations for decomposing effective unemployment are likely to yield results that differ from those obtained using the univariate filters. More interestingly, knowing the determining factors behind the NRU might allow the policymakers acting directly on them with the aim of reducing natural unemployment.

The second issue to be highlighted is that the evolution of the SF estimations of natural unemployment is compatible with the hypothesis of hysteresis in the labor market, since a certain "cyclical influence" can be seen in this component of unemployment. Aysun et al. (2014), which is the closest paper to ours, reach a similar conclusion when discussing the cyclical pattern of their measure of structural unemployment. According to this hypothesis, the NRU is affected by economic ups and downs in the labor market and may be affected to a certain degree by past levels of unemployment[37]. This finding has already been supported for the case of regional labor markets in Spain by García-Cintado et al. (2015). Being aware that also the NRU is affected to some extent by the business cycle is important from an economic policy standpoint. This observation should encourage policymakers to act counter-cyclically with the aim of diminishing the cyclical variations not only of the cyclical unemployment but the natural unemployment too.

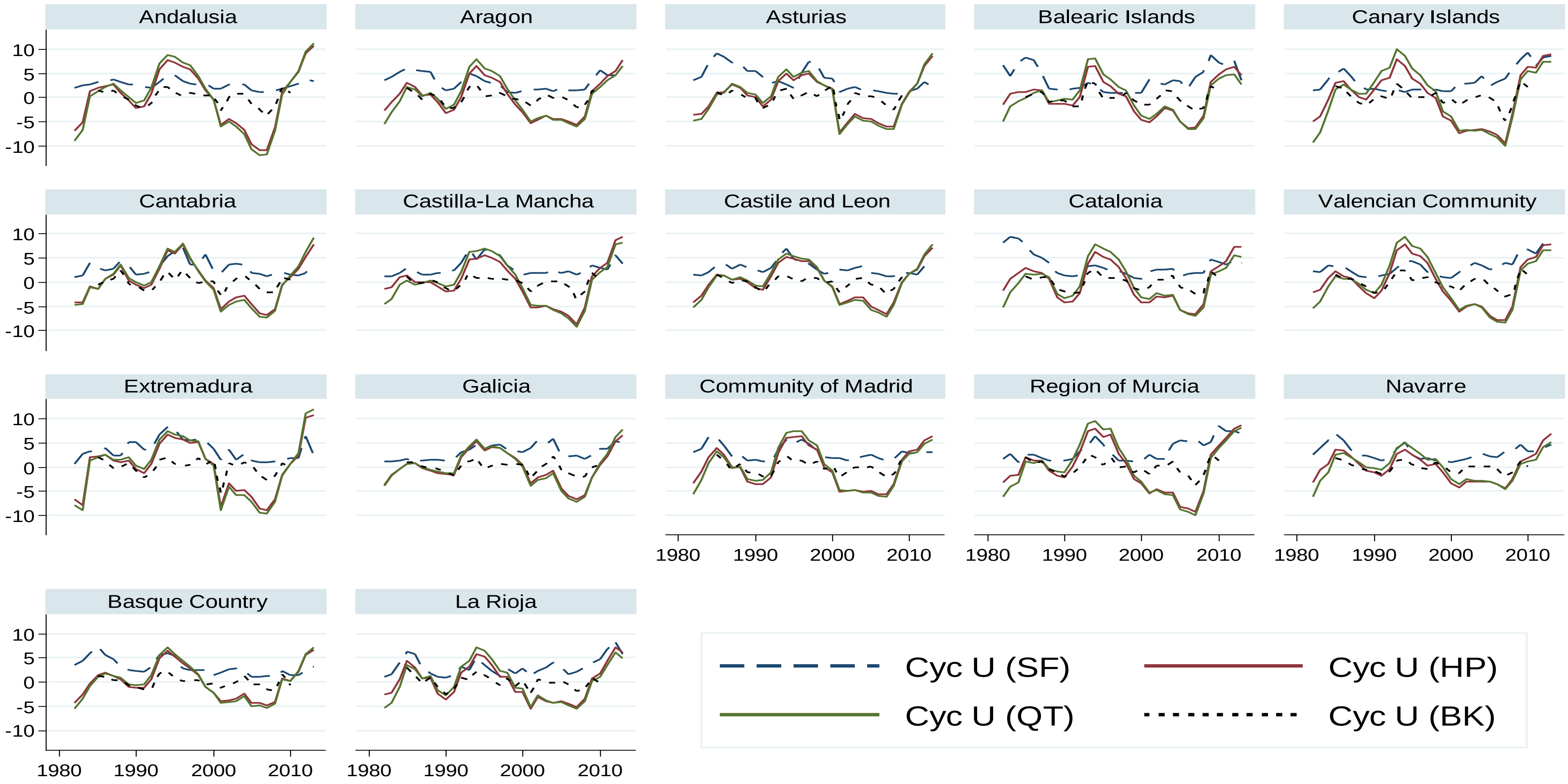
[37] The works of Blanchard and Summers (1986, 1987) set out the theory of hysteresis in the labor market. See Røed (1997) for a review of said theory.

Figure 4. Natural unemployment by estimation method and autonomous community (1982-2013)



<u>Notes:</u> "Nat U (SF)", refers to the SF estimations. "Nat U (HP)", refers to estimations obtained from the HP Filter. "Nat U (QT)", refers to estimations obtained from the QT decomposition. , "Nat U (QT)" refers to estimations obtained from the BK Filter.
<u>Source:</u> Authors' own.

Figure 5. Cyclical unemployment by estimation method and autonomous community (1982-2013)



Notes: "Cic U (SF)", refers to the SF estimations. "Cic U (HP)", refers to estimations obtained from the HP filter. "Nat U (QT)", refers to estimations obtained from the QT decomposition. , "Cic U (QT)" refers to estimations obtained from the BK Filter.
Source: Authors' own.

Thirdly, according to the SF estimations, there is greater scope for action for aggregate demand policies when reducing cyclical unemployment compared to the estimations offered by the univariate filters. This statement is true in general terms for all Spanish regions since, in line with table 5 of the Appendix, the SF estimations show positive mean values for the whole period unlike the values given by the univariate filters. Put it another way, according to our estimates stronger fiscal and monetary policies are required, particularly during upturns. At first sight, this last statement could seem a bit strange since in many countries cyclical unemployment is not an issue during booms as a consequence of their low levels in total unemployment. However, it should not be forgotten that in Spain, and after a long period of sustained economic growth, the lowest unemployment rate for the whole country was about 8 percentage points in 2007. What is more, in some Spanish regions such a figure was a two-digit unemployment rate.

Finally, from our empirical analysis, several regional economic policy prescriptions may be extracted. Figures 4 and 5 are a helpful tool for regional policymakers in order to understand the relative importance of natural and cyclical unemployment in each Spanish region, which would allow them to act accordingly. Some comments in this vein that could be made are that the mean aggregate values indicate that Asturias, the Balearic Islands and Extremadura are the autonomous communities in which cyclical unemployment might have been reduced notably during the period 1982-2013. This situation occurs particularly during the first period (1982-1993) and the third (1999-2010), partially coinciding with economic upturns. As it has been already pointed out, the SF estimations seems to indicate that during growth periods greater use might be made of aggregate demand policies so as to continue reducing the cyclical unemployment which, according to other methods, is deemed natural unemployment. These results are not as clear during the second (1994-1998) and fourth period (2010-2013) in which a certain mean underestimation of natural unemployment can be seen when applying the HP and QT filters for several autonomous communities[38]. These periods partially coincide with periods of economic recession. Between 1994 and 1998, these regions are: Andalusia, Aragon, the Balearic Islands, the Canary Islands, Catalonia, the Valencian Community, the Community of Madrid (only in the case of QT), the Region of Murcia, Navarre (only in the case of QT) and La Rioja, whilst for the period 2011-2013 they were Andalusia, Aragon (only for the case of HP), Asturias, Cantabria, Castilla La Mancha, Castile and Leon, Catalonia (only for the case of HP), Extremadura, the Community of Madrid, Navarre (only for the case of HP) and the Basque Country. Said underestimation of natural unemployment lends greater weight to the importance of cyclical unemployment, which can be clearly seen in figure 5 and in the mean values of tables A4 and A5 of the Appendix[39]. These results would seem to indicate that, in agreement with the SF estimations, during downturns the natural unemployment increases and less cyclical unemployment may be reduced by implementing aggregate demand policies. Nevertheless, provided that cyclical unemployment still remains positive, fiscal and monetary economic policies have room for maneuver.

[38] The previous result is qualified to a large degree when compared to the estimations offered by the BK filter for the period 1994-1998, in which the Balearic Islands is the autonomous community whose natural unemployment is underestimated by a larger extent.
[39] This hypothesis is supported for the case of the HP and QT estimates.

6. Conclusions

The present work pursues two objectives. The first is to decompose the effective unemployment rates of the 17 autonomous communities in Spain over the period 1982-2013 into two components, so-called natural unemployment (U_{it}^{NR}) and cyclical unemployment (U_{it}^{C}). To do this, a stochastic cost frontier has been estimated, here interpreted as a measure of the natural component, together with a non-zero mean error, which corresponds to the cyclical component. The results underscore the fact that the bulk of effective unemployment is due to factors associated to the natural more than to the cyclical unemployment. It can also be seen how it is natural unemployment which mainly accounts for the rise of effective unemployment during the "Great Recession".

The second goal is to determine whether, for the natural unemployment and for the cyclical unemployment, the SF estimations yield different results to those obtained using the HP Filter, the BK Filter, and the QT decomposition. Our findings bring to light the existence of differences in the estimations between the various techniques applied. Said differences are due to variations in the ways the univariate filters and SF estimations are constructed. It should be remembered that our estimates are based on a multivariate approach that uses information based on economic theory. This allows us to identify those factors influencing more the NRU, which is an advantage over the univariate techniques, from our standpoint.

The above mentioned differences might have important implications for economic policy. Firstly, and according to our methodological proposal, natural unemployment is overestimated for the period 1982-2013 when applying the HP Filter, the QT decomposition and the BK Filter if compared to the SF estimations. Moreover, when quantifying natural unemployment, the estimates given by the filters fail to take into account the impact of the business cycle, particularly for the HP Filter and the QT decomposition, and to a less extent for the BK filter. As a result, the phenomenon of "hysteresis" is not accurately reflected by means of this type of univariate techniques, whereas it is more properly captured through the SF estimations. Thus, policymakers' decisions might be flawed if the scale of natural unemployment is not identified correctly. In the same way, erroneous or inefficient economic policies may be applied.

In the second and fourth, previously determined, sub-periods, which are mainly downturn or low growth periods from a business cycle perspective, the mean values of natural unemployment estimated by SF exceed those of the statistical filters, in some communities. This would imply that should the policymakers followed the "signals" provided by the filters, the aggregate demand policies implemented would be too strong. However, during upturns the statistical filters underestimate cyclical unemployment. Therefore, during upturns, where the filters yield negative cyclical unemployment rates, the SF estimations still offer room for maneuver to reduce cyclical unemployment by implementing aggregate demand policies. Put it in other words, SF estimations prescribe more intensive fiscal and monetary expansions during the upturns than the conventional view (i.e. the HP Filter, the QT decomposition and to a lesser extent the BK Filter). Although cyclical unemployment might not be considered an issue during upturns in many countries, it should not be forgotten that a two-digit unemployment rate is quite common in many Spanish regions during booms.

Also from an economic policy perspective, the results set out in the present work might help policymakers when making the decision to implement economic policies affecting the labor markets. Regardless of the method used, natural unemployment is the principal cause of high rates of effective unemployment. In this way SF estimations also seem to point to the same conclusion. Although it should also be pointed out that all in all the SF estimations for the NRU over the whole business cycle are lower than those of the univariate filters.

Based on this, the insistence should be on measures which focus on aggregate supply policies. Some such measures might be aimed at enhancing workers' human capital. This would help reduce natural unemployment in its structural component. Fostering interregional worker mobility and introducing changes in collective wage bargaining mechanisms (amending the system for reviewing wages in accordance with work productivity) would help curb natural unemployment in its structural component. On the other hand, introducing improvements in public employment services and in the way information is provided concerning vacancies would help reduce jobseekers job-search time. This would improve matching efficiency in regional labor markets and cut natural unemployment in its frictional component.

However, our main conclusion is that cyclical unemployment might be understated when it is computed by means of the popular HP Filter, BK Filter and QT decomposition according to our SF estimations, particularly during upturns. Two types of lines of action could be drawn from this observation. First, efforts should focus on developing a productive model that would attract labor towards sectors which are less dependent on the business cycle. In order to implement these latter measures, labor institutions should be set up to promote R&D that would make the economic structure more dynamic at a regional and aggregate scale. Second, there is room for implementing more active monetary and fiscal policies, since cyclical unemployment could be higher than previously thought. This is especially true during upturns. In this vein, it ought to be remembered that while in many countries cyclical unemployment is not an issue during booms, in many Spanish regions (e.g. Andalusia, Extremadura, Canary Islands …) it is a real problem associated with two-digit effective unemployment rates.

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APPENDIX

Table A1. Description of variables and data sources

Variable	Definition	Source
Unemployment rate in region i in year t (U_{it})	$U_{it} = \frac{U_{it}}{AP_{it}} * 100$ U_{it} : Total number of those unemployed in region i in period t. AP_{it} : Total active population in region i in period t.	Labor Force Survey (EPA), published by the National Institute of Statistics (INE)
Female activity rate in region i in year t (FAR_{it})	$FAR_{it} = \frac{AFP_{it}}{FPOP\ 16-65_{it}} * 100$ AFP_{it} : Total active female population in region i in period t. $FPOP\ 16-65_{it}$: Female population of working age in region i in period t.	Labor Force Survey (EPA), published by the National Institute of Statistics (INE)
Percentage of youth population in region i in year t (PYP_{it})	$PYP_{it} = \frac{YOUNG_{it}}{POP_{it}} * 100$ $YOUNG_{it}$: Total population of 16 to 24 year-olds in the region i in period t. POP_{it} : Total population in region i in period t.	Labor Force Survey (EPA), published by the National Institute of Statistics (INE)
Number of employed in the agricultural sector in region i in year t ($Agri_{it}$)	$Agri_{it} = \frac{AGRI_{it}}{TEmp_{it}} * 100$ $AGRI_{it}$: Total number of those employed in the agricultural sector in region i in period t. $TEmp_{it}$: Total number of employed in the region i in period t.	Valencian Institute of Economic Research (IVIE)
Number of employed in the manufacturing sector in region i in year t (Man_{it})	$Ind_{it} = \frac{MAN_{it}}{TEmp_{it}} * 100$ MAN_{it}: Total number of those employed in the manufacturing sector in region i in period t. $TEmp_{it}$: Total number of employed in region i in period t.	Valencian Institute of Economic Research (IVIE)
Number of employed in the service sector in region i in year t ($Serv_{it}$)	$Serv_{it} = \frac{SERV_{it}}{TEmp_{it}} * 100$ $SERV_{it}$: Total number of those employed in the service sector in region i in period t. $TEmp_{it}$: Total number of those employed in region i in period t.	Valencian Institute of Economic Research (IVIE)

Source: Authors' own.

Table A2. Mean value and deviation of the variables used in the estimation

	Unemployment rate	Female activity rate	Percentage of youth population	Agriculture	Manufacturing	Services
Andalusia	25.87	36.26	18.57	12.90	11.97	63.42
	(6.69)	(9.54)	(3.71)	(4.61)	(2.56)	(7.33)
Aragon	12.06	38.24	14.23	10.58	22.96	56.64
	(4.70)	(9.08)	(2.71)	(4.91)	(2.76)	(6.87)
Asturias	16.11	35.88	13.86	11.77	16.63	57.64
	(4.64)	(5.72)	(3.38)	(6.59)	(2.46)	(10.32)
Balearic Islands	12.64	45.70	15.77	4.04	11.76	70.72
	(4.84)	(9.55)	(2.75)	(3.29)	(4.37)	(7.32)
Canary Islands	20.73	42.49	18.74	7.49	6.99	73.36
	(6.77)	(8.66)	(4.69)	(4.35)	(1.80)	(6.57)
Cantabria	15.18	37.30	15.24	11.15	20.31	57.43
	(4.96)	(7.76)	(3.50)	(7.03)	(3.21)	(9.11)
Castilla-La Mancha	15.66	33.85	16.42	14.55	18.65	52.73
	(5.39)	(9.62)	(2.76)	(7.61)	(2.15)	(8.69)
Castile and Leon	15.35	36.02	14.78	14.79	16.84	56.16
	(4.19)	(7.19)	(3.36)	(7.81)	(0.94)	(8.19)
Catalonia	15.33	44.84	15.42	3.53	27.82	58.71
	(5.48)	(8.48)	(3.26)	(1.52)	(6.22)	(7.38)
Valencian Community	17.19	41.52	16.36	7.05	24.00	58.74
	(5.66)	(7.73)	(3.39)	(3.75)	(4.77)	(7.33)
Extremadura	23.75	33.96	17.06	18.54	9.78	58.11
	(6.11)	(8.20)	(3.00)	(7.72)	(0.66)	(7.60)
Galicia	14.00	42.79	14.76	22.78	16.00	50.65
	(3.90)	(3.25)	(3.24)	(13.04)	(1.62)	(11.51)
Community of Madrid	14.14	43.20	16.49	1.00	16.15	73.52
	(4.95)	(10.90)	(3.76)	(0.32)	(5.16)	(5.44)
Region of Murcia	17.58	39.77	18.45	14.54	17.90	56.43
	(5.94)	(8.46)	(3.53)	(3.71)	(3.88)	(6.30)
Navarre	11.27	40.53	15.31	7.78	29.61	53.26
	(4.39)	(9.33)	(3.37)	(3.45)	(3.40)	(5.79)
Basque Country	15.93	41.07	15.26	2.93	29.24	59.42
	(5.78)	(7.67)	(4.35)	(1.64)	(5.89)	(7.09)
La Rioja	11.65	37.54	14.72	10.84	29.91	49.98
	(4.42)	(9.60)	(2.67)	(4.52)	(3.42)	(6.38)
Total	16.14	39.47	15.97	10.37	19.21	59.23
	(6.52)	(9.06)	(3.67)	(8.07)	(7.80)	(10.33)

Notes: Information provided by the INE and the IVIE. In brackets the standard deviations of the variables.
Source: Authors' own.

Table A3: Econometric specifications

	Specification 1	Specification 2
C	-153.867*** (-19.10)	-151.178*** (-17.54)
FAR	0.248*** (4.72)	0.274*** (4.50)
PYP	1.337*** (7.4)	1.234*** (5.67)
Agri	1.350*** (18.77)	1.315*** (15.8)
Man	1.270*** (13.1)	1.240*** (11.98)
Serv	1.765*** (23.95)	1.776*** (23.75)
D2001	-3.356*** (-4.90)	-3.387*** (-4.92)
T		-0.094 (-0.83)
Cost Frontier	5.08 0.012**	4.38 0.018**
No. of obs	544	544

Notes: The dependent variable is the aggregate unemployment rate in each autonomous community. All estimations include the observations from the 17 autonomous communities.
"Cost Frontier", refers to the test of maximum likelihood for determining whether a cost frontier exists or not.
*, ** and *** indicate significance at 10%, 5% and 1%, respectively.
In brackets the value corresponding to the "t" statistic.
The results associated to fixed effects are not shown.
Source: Authors' own.

Table A4: Descriptive statistics of the natural unemployment of the autonomous communities (1982-2013)

Autonomous Community	Mean values (1982-2013)				Standard deviation (1982-2013)				Mean values (1982-1993)				Mean values (1994-1998)				Mean values (1999-2010)				Mean values (2011-2013)			
	SF	HP	QT	BK	SF	HP	QT	BK	SF	HP	QT	BK	SF	HP	QT	BK	SF	HP	QT	BK	SF	HP	QT	BK
AND	23.2	25.8	25.8	25.2	5.3	1.5	1.5	5.7	24.5	27.6	27.5	28.6	28.2	26.2	25.3	31.4	18.2	24.1	24.6	20.1	29.6	25.2	24.8	N.A
ARA	8.9	12.0	12.0	11.1	2.9	1.5	2.3	3.6	8.7	13.5	13.7	13.5	12.1	11.2	9.9	14.1	6.4	10.7	10.7	7.9	13.6	13.1	14.1	N.A
AST	12.3	16.1	16.1	15.7	3.9	1.2	1.1	3.9	10.3	17.4	17.3	18.2	15.0	16.5	15.9	20.0	11.6	14.8	15.1	12.0	19.0	15.3	14.9	N.A
BAL	8.8	12.6	12.6	11.5	4.6	1.8	2.9	2.9	8.1	12.3	12.6	12.6	14.6	11.0	9.6	12.9	5.6	12.5	12.4	10.0	15.2	16.9	18.5	N.A
CAN	17.2	20.7	20.7	19.5	6.4	1.9	3.1	5.3	20.8	21.9	22.1	23.9	22.1	19.2	17.4	21.6	10.3	19.3	19.4	15.3	22.2	23.9	25.2	N.A
CANT	12.2	15.1	15.1	15.0	3.9	1.8	1.8	4.6	14.3	17.0	16.9	17.9	15.1	16.2	15.9	20.5	7.8	13.5	14.0	10.6	16.2	12.6	11.6	N.A
CLM	12.7	15.6	15.6	14.5	4.2	1.6	2.4	3.3	13.1	15.0	15.2	15.3	12.4	14.6	13.2	18.2	10.0	15.6	15.7	12.4	22.3	19.8	20.8	N.A
CLE	12.5	15.3	15.3	15.0	3.1	1.1	1.0	3.6	13.4	16.5	16.4	17.2	14.6	15.8	15.3	19.3	9.6	14.1	14.5	11.6	17.1	14.4	14.0	N.A
CAT	11.8	15.3	15.3	14.0	3.7	2.5	3.5	4.2	12.5	18.1	18.4	17.3	15.6	14.1	12.5	17.0	8.4	13.0	12.9	10.4	16.5	15.2	17.0	N.A
VAL	13.9	17.1	17.1	16.1	4.8	1.3	2.2	4.2	16.6	18.0	18.2	18.3	17.6	16.2	14.8	20.1	8.7	16.1	16.2	12.7	17.8	19.5	20.5	N.A
EXT	20.2	23.7	23.7	23.4	3.8	1.2	1.0	5.0	21.1	24.9	24.8	26.3	21.9	24.4	23.9	29.1	17.0	22.4	22.9	18.8	26.5	22.9	22.0	N.A
GAL	10.9	13.9	13.9	13.8	3.0	1.0	1.0	2.7	12.1	13.0	12.8	13.6	13.4	14.6	14.4	18.0	7.9	14.4	14.8	12.2	14.1	15.2	14.3	N.A
MAD	11.1	14.1	14.1	13.3	3.3	2.0	2.3	4.2	12.9	16.4	16.5	15.8	13.1	13.9	12.9	17.9	7.6	12.2	12.3	9.6	14.7	13	13.7	N.A
MUR	14.1	17.5	17.5	16.6	5.7	1.1	1.7	4.5	17.1	18.2	18.3	19.1	18.5	17.0	15.7	21.0	8.1	16.6	16.9	12.9	18.1	19.6	20.2	N.A
NAV	8.3	11.2	11.2	10.3	3.2	2.4	3.2	3.7	10.6	14.0	14.3	14.1	9.8	10.2	9.0	11.4	4.6	9.0	8.9	7.0	10.8	10.7	12.1	N.A
BAC	12.8	15.9	15.9	15.6	3.6	4.3	4.3	5.7	15.6	20.6	20.6	20.9	16.2	16.7	16.2	19.8	8.7	12.2	12.6	9.8	12.7	10.0	9.7	N.A
RIO	8.4	11.6	11.6	10.7	3.2	1.2	2.1	3.1	10.4	12.5	12.7	12.8	10.9	10.7	9.5	13.2	4.9	10.6	10.7	8.1	10.4	13.3	14.4	N.A

Notes: AND: Andalusia. ARA: Aragon. AST: Asturias. BAL: Balearic Islands. CAN: Canary Islands. CANT: Cantabria. CLM: Castilla-La Mancha. CLE: Castile and Leon. CAT: Catalonia. VAL: Valencian Community. EXT: Extremadura. GAL: Galicia. MAD: Community of Madrid. MUR: Region of Murcia. NAV: Navarre. BAC: Basque Country. RIO: La Rioja. "SF", refers to the SF estimations. "HP", refers to estimations obtained from the HP Filter. "QT", refers to estimations obtained from the QT decomposition. "BK", refers to estimations obtained from the BK Filter. No values are shown for the BK Filter in the fourth period due to the actual construction of the filter, which establishes the loss of a certain number of data at the start and at the end of the period studied. The first period for the case of the BK Filter is 1985-1993, due to the actual construction of the filter which establishes the loss of a certain number of data at the start and at the end of the period studied.
Source: Authors' own.

Table A5: Descriptive statistics of the cyclical unemployment of the autonomous communities (1982-2013)

Autonomous Community	Mean values (1982-2013)				Standard deviation (1982-2013)				Mean values (1982-1993)				Mean values (1994-1998)				Mean values (1999-2010)				Mean values (2011-2013)			
	SF	**HP**	**QT**	**BK**	**SF**	**HP**	**QT**	**BK**	**SF**	**HP**	**QT**	**BK**	**SF**	**HP**	**QT**	**BK**	**SF**	**HP**	**QT**	**BK**	**SF**	**HP**	**QT**	**BK**
AND	2.6	1.7E-07	-1.8E-07	-0.1	0.8	5.8	6.5	1.6	2.7	-0.1	-0.1	0.0	3.5	6.1	7.0	1.0	1.9	-4.5	-5.0	-0.5	3.2	8.3	8.7	N.A
ARA	3.1	9.3E-09	3.1E-09	-0.0	1.6	3.8	4.0	1.3	4.1	0.1	-0.1	-0.0	2.8	3.8	5.0	0.8	2.0	-3.1	-3.2	-0.4	4.3	5.9	4.8	N.A
AST	3.7	1.1E-07	4.3E-08	-0.0	2.4	4.0	4.4	1.5	5.6	-0.1	-0.0	0.1	4.7	4.2	4.7	0.6	1.7	-3.1	-3.5	-0.4	2.3	5.9	6.3	N.A
BAL	3.7	1.2E-08	-3.1E-09	-0.1	2.5	3.7	3.8	1.6	4.2	0.4	0.1	-0.1	1.3	2.5	4.0	0.6	3.8	-2.8	-2.8	-0.4	5.8	5.5	4.0	N.A
CAN	3.4	-7.1E-08	-1.3E-07	0.0	2.4	5.4	5.9	1.6	2.6	1.2	1.0	0.4	1.4	2.8	4.5	0.4	4.0	-4.4	-4.5	-0.4	7.7	7.9	6.5	N.A
CANT	2.9	-1.8E-08	-1.3E-07	-0.0	1.5	4.1	4.6	1.3	2.5	-0.3	-0.1	-0.1	5.3	5.5	5.7	1.1	2.5	-3.2	-3.7	-0.4	2.1	5.2	6.2	N.A
CLM	2.9	-5.9E-08	-1E-07	-0.1	1.6	4.5	4.8	1.2	2.4	0.1	-0.1	-0.1	5.3	4.3	5.7	0.7	2.1	-3.7	-3.8	-0.4	4.0	7.3	6.3	N.A
CLE	2.7	-3.1E-08	4.0E-08	-0.0	1.2	3.6	4.0	1.1	2.8	-0.1	-0.0	0.1	4.4	4.2	4.7	0.7	2.0	-2.9	-3.3	-0.4	2.4	5.0	5.4	N.A
CAT	3.4	2.8E-08	-6.8E-08	-0.1	2.3	4.1	4.1	1.5	4.8	-0.1	-0.4	-0.2	2.5	4.0	5.5	1.1	2.2	-3.1	-3.0	-0.4	4.0	6.3	4.5	N.A
VAL	3.2	1.2E-08	-1.6E-07	-0.1	1.8	4.8	5.1	1.5	2.1	0.2	-0.1	-0.0	3.1	4.7	6.2	0.9	3.4	-3.8	-3.9	-0.4	6.8	6.9	5.8	N.A
EXT	3.5	-1.1E-07	1.1E-07	-0.1	2.1	5.4	6.0	1.7	3.5	-0.1	0.1	0.1	6.5	5.7	6.2	1.0	2.1	-4.2	-4.8	-0.6	3.6	7.7	8.5	N.A
GAL	3.0	9.3E-09	-3.1E-08	-0.1	1.4	3.4	3.7	1.1	1.7	-0.3	-0.1	0.0	4.1	3.9	4.0	0.5	3.4	-2.5	-2.9	-0.3	4.7	4.7	5.5	N.A
MAD	2.9	3.4E-08	-1.9E-07	-0.0	1.5	4.1	4.3	1.3	3.0	-0.4	-0.6	-0.1	4.8	5.3	6.3	1.2	2.0	-3.0	-3.1	-0.4	2.9	5.1	4.5	N.A
MUR	3.4	-8.7E-08	1E-07	-0.0	2.2	5.1	5.6	1.5	2.1	0.3	0.1	0.1	3.3	4.8	6.1	0.8	3.9	-4.2	-4.5	-0.5	7.2	7.5	6.9	N.A
NAV	2.9	-8.4E-08	-1.5E-08	-0.0	1.4	2.9	2.9	1.0	3.4	0.3	0.1	0.1	2.4	1.7	2.9	0.5	2.4	-2.3	-2.2	-0.3	3.9	4.9	3.5	N.A
BAC	3.0	-5.9E-08	-1.8E-08	-0.0	1.6	3.4	3.8	1.1	4.2	0.0	0.0	0.0	3.7	3.9	4.4	0.8	1.7	-2.8	-3.1	-0.4	2.3	4.7	5.0	N.A
RIO	3.1	6.2E-08	-4.3E-08	-0.0	1.8	3.7	3.8	1.3	2.7	0.1	-0.1	0.1	3.0	3.3	4.4	0.8	2.7	-2.9	-3.0	-0.4	7.0	5.8	4.8	N.A

Notes: AND: Andalusia. ARA: Aragon. AST: Asturias. BAL: Balearic Islands. CAN: Canary Islands. CANT: Cantabria. CLM: Castilla-La Mancha. CLE: Castile and Leon. CAT: Catalonia. VAL: Valencian Community. EXT: Extremadura. GAL: Galicia. MAD: Community of Madrid. MUR: Region of Murcia. NAV: Navarre. BAC: Basque Country. RIO: La Rioja. "SF", refers to the SF estimations. "HP", refers to estimations obtained from the HP Filter. "QT", refers to estimations obtained from the QT decomposition. "BK", refers to estimations obtained from the BK Filter. No values are shown for the BK Filter in the fourth period due to the actual construction of the filter which establishes the loss of a certain number of data at the start and at the end of the period studied. The first period for the case of the BK Filter is 1985-1993, due to the actual construction of the filter which establishes the loss of a certain number of data at the start and at the end of the period studied.
Source: Authors' own.