DISCUSSION PAPER SERIES

IZA DP No. 5838

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July 2011

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

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ABSTRACT

The NRU and the Evolution of Regional Disparities in Spanish Unemployment*

On both theoretical and empirical grounds, this paper provides evidence that refutes the natural rate of unemployment (NRU) hypothesis as an explanation of the evolution of regional disparities in the unemployment rate. We first present our analytical framework, which follows the chain reaction theory (CRT) of unemployment and argues that (i) a system of interactive labour market equations, rather than a single-equation unemployment rate model, is better equipped to accommodate unemployment dynamics, and (ii) due to the interplay of frictions and growth in labour markets, the NRU ceases to be an attractor of the unemployment rate time path. We then provide evidence that the Spanish economy is characterised by large and persistent disparities in the regional unemployment rates. Through standard kernel density tecnhiques, we demonstrate the existence of marked differences between two groups of high and low unemployment regions that remain stable in their composition through time. Finally, we review our empirical labour market model for each group of regions and evaluate the corresponding natural rates. Our findings confirm that the evolution of regional disparities cannot be attributed to disparities in the natural rates, given that these, although different, do not act as an attractor of unemployment. Thus, the NRUs offer little help in the formulation of labour market policies.

JEL Classification: R23, J64

Keywords: regional unemployment, disparities, kernel, natural rate, frictional growth

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* Comments from the GAME research group members are acknowleged. All errors are our own responsibility. Roberto Bande acknowledges financial support from Xunta de Galicia, through grant 10SEC242003PRR.

1 Introduction

The existence and persistence of large regional unemployment disparities has been a recurrent theme in the literature. Many views have been put forward to explain why regional unemployment rates can diverge for long periods within countries. The prevailing idea seems to be that disparities reflect regional differences in the long-run equilibrium unemployment rates, namely the natural rates of unemployment. According to Marston (1985), regional unemployment disparities may reflect either an equilibrium outcome, due to differences in the regional natural rates of unemployment (determined by demand, supply and institutional variables which evolve steadily through time), or a disequilibrium outcome, resulting from differences in the regional labour markets adjustment to common shocks and giving rise to a polarisation effect.

Much of the research has tried to disentangle these views and to provide explanations in favour of the equilibrium or the disequilibrium approaches (see Pekhonen and Tervo, 1998, or López-Bazo et al., 2005, for instance). Natural rates may diverge at the regional level due to differences in real unemployment benefits, the composition of the labour force (young/old workers, male/female, ethnic minorities, skilled/unskilled, etc.), regional ammenities, etc. There are thus many candidates which can potentially explain the underlying differences in the regional natural rates.

The NRU approach to the explanation of unemployment disparities relies heavily on two presumptions, not always stated clearly. First, the very own existence of a natural rate. Second, that the NRU is a reference point, i.e. the natural rate acts as an attractor around which unemployment evolves. In this case, the design of labour market policies is straightforward: policies should aim at reducing the regional natural rates, mainly through supply side policies, given that in the standard literature demand side innovations do not exert significant effects on the natural rate.

In this paper we approach the regional unemployment issue from a different perspective, that of the chain reaction theory of unemployment. The CRT views the evolution of unemployment as the interplay of dynamics and "shocks" within a labour market system of equations.[1] While the NRU has become the incumbent way of thinking, various strands of the macro-labour literature have opined that an important dimension of the unemployment problem is that employment, wage setting, and labour force participation decisions are characterised by significant lags. The unemployment predictions of the CRT multi-equation models lie in stark contrast to those of the single-equation NRU ones and structuralist theories.[2] We demonstrate that due to the phenomenon of frictional growth, i.e. the interplay of lagged adjustment processes and exogenous growing variables in labour markets, the natural rate cannot be regarded as an attractor of the unemployment trajectory.

[1] The CRT framework was originally developed by Marika Karanassou and Dennis J. Snower in a series of papers. See Karanassou, Sala and Snower (2010) for an overview of the chain reaction approach with comparison to single-equation unemployment rate models. As far as the latter is concerned, Elhorst (2003) concludes that the standard approach of estimating reduced form unemployment equations is poorly equipped to determine the factors responsible for regional unemployment disparities, since these disparities are the outcome of simultaneous labour demand, wage setting, and labour supply relations.

[2] Phelps (1994) offers a comprehensive account of the structuralist theory.

Despite the popularity of the NRU approach, the number of papers providing estimates of the natural rate at the regional level is scant. This is surprising, since many of the regional-based labour market policies are designed having the natural rate hypothesis in the background. In particular, Wall and Zoega (2004) argue that the design of proper macro labour market policies should take into account the regional structure of the economy, since the aggregate natural rate of unemployment (key to modern monetary policy implementation) may depend directly on the dispersion of economic activity across regions.

Miller (1987) and Johnson and Kneebone (1991), using single-equation models, regress the unemployment rates of Canada on labour supply variables (which drive the natural component of unemployment) and cyclical ones. Both papers find that Canadian disparities in unemployment may well be explained by different regional NRUs. A similar conclussion is found for the US states by Partridge and Rickman (1997). They estimate differences in the regional NRUs with respect to the national NRU and find strong and persistent differences in the regional NRUs due to regional ammenities, crime rates, education and home ownership. Murphy and Payne (2003) estimate a somewhat different model for the US and find that changes in the national NRU are due to regional effects. These regional trends in the underlying natural rates are driven mainly by wages, education, and young population. Remarkably, they find no significant effects of unionization, unemployment benefits, and industrial employment structure on regional NRUs.

All of these estudies share a similar emprical approach, namely the estimation of a reduced form equation for the regional unemployment rate. Other authors have explored different empirical avenues. For instance, Pehkonen and Tervo (1998) compute long-run unemployment rates for the Finish regions and municipalities with autoregressive and moving-average models. For the regional data they find persistent disparities, due to different NRUs, and a positive correlation between unemployment persistence and the natural rates. However, with local data this correlation weakens and the disparities are less persistent. Groenewold and Hagger (2003) estimate regional natural rates for the Australian regions through structural vector autoregressions, and find that disparities are due to different regional NRUs. Nevertheless, depending on the region considered, the authors identify very different degrees of linkages between actual and natural rates. Finally, Capó and Gómez (2006) find different estimates of the regional natural and non accelerating inflation rates of unemployment in Spain, arguing that the levels of equilibrium regional unemployment depend on the estimation technique and sample period.

This work, instead of estimating a single-equation NRU model, addresses regional disparities by taking into account the interplay between lags and growth (through the estimation of a CRT multi-equation labour market model with interactive dynamics), and then deriving the univariate representation of unemployment.

Frictional growth is a key difference between the CRT and NRU methodologies that leads to opposing views regarding market conditions: while the short-run (cyclical) and long-run (natural) unemployment rates are interdependent in CRT models, they are compartmentalised in NRU ones (as made aparent by the literature reviewed above). Consequently, the disparity in the identification of the driving forces of the unemployment rate is substantial: whereas the CRT recognises the major influence of growth factors (e.g. capital accumulation), the NRU restricts its attention to wage-push determinants (e.g. benefits) or supply side shocks. Put it differently: while the NRU focuses on the determinants of the natural rate (basically labour market institutions in the tradition of Blanchard and Wolfers, 2000, Nickell and Nunziatta, 2006), the CRT focuses on the determinants of actual unemployment rates and the contribution of the exogenous variables to its evolution.

Therefore, when the chain reaction theory is applied to the investigation of regional unemployment disparities, both the explanation and policy implications differ dramatically from the standard NRU approach. While most of the reviewed papers explain disparities in terms of estimates of the natural rate, the CRT implies that the NRU may no longer be a reference point (i.e. a value towards which the actual rate gravitates), and thus its explanatory power becomes questionable. The CRT provides an alternative and rigorous explanation: it is the interplay between lagged adjustment processes and growing variables that drives regional disparities through time. Since Spain is characterised by large and persistent regional unemployment disparities, in what follows we apply the CRT methodology to Spanish data.

Here is the structure of the paper. Section 2 presents our analytical framework, and discusses the main differences between the NRU and CRT approaches. Section 3 portrays the evolution of Spanish disparities since 1980, and classifies the regions into two groups of high and low relative unemployment rates. Section 4 provides the econometric results of the labour market system for each group of regions. Section 5 evaluates the NRUs corresponding to the empirical models and shows that Spanish regional unemployment does not evolve around its natural rates. Finally, Section 6 concludes.

2 Natural Rate versus Chain Reaction of Unemployment

2.1 NRU Models

Standard models of unemployment dynamics are commonly derived in terms of a wage-price spiral that effectively determines the equilibrium unemployment rate in the long run, which is dubbed the natural rate of unemployment. We outline the salient characteristics of the NRU approach by using a rather simplistic type of model.

Consider that real wages are set by wage bargaining, such that the wage equation may be written as[3]

$$W_t - P_t^e = \alpha_0 - \alpha_1 u_t + \boldsymbol{\alpha}_2 \mathbf{X}_t, \quad (1)$$

where P_t is the log of nominal wages, P_t^e is the log of expected prices, u_t is the unemployment rate (not in logs), X_t is a (column) vector of exogenous variables in logarithms that affect wage setting (wage-push variables, such as minimum wages, unemployment benefits, etc.), the α's are positive constants, and α_2 is a (row) vector of positive parameters.

Prices are set by firms operating in non competitive markets as a markup over their labour

[3] Error terms are omitted for ease of exposition.

unit costs. Thus, the price equation may be written as

$$P_t = \mu_0 + W_t, \tag{2}$$

where μ_0 is a function of the price elasticity of product demand.

Writing both equations (1) and (2) in terms of the nominal wage and combining them gives

$$\alpha_0 + P_t^e - \alpha_1 u_t + \boldsymbol{\alpha}_2 \mathbf{X}_t = P_t - \mu_0,$$

and solving for the unemployment rate we get the following reduced form unemployment rate equation:

$$u_t = \frac{\alpha_0 + \mu_0}{\alpha_1} + \frac{(P_t^e - P_t)}{\alpha_1} + \frac{\boldsymbol{\alpha}_2 \mathbf{X}_t}{\alpha_1}. \tag{3}$$

Some key implications of the reduced form unemployment rate equation (3) should be pointed out.

First, as Friedman argued in his influential 1968 paper, since expectations must be correct in the long run, unemployment must be at its natural level when the exogenous variables reach their long-run values, $\mathbf{X}^{LR}$. Therefore, the natural rate of unemployment is

$$u_t^n = \frac{\alpha_0 + \mu_0 + \boldsymbol{\alpha}_2 \mathbf{X}^{LR}}{\alpha_1}. \tag{4}$$

Clearly, as long as expectations are not fulfilled, unemployment will diverge from its natural rate. In other words, the main reason for unemployment being away from its long-run equilibrium rate is the existence of persistent errors in expectations. Put differently, in the short run unemployment may fluctuate around its natural rate due to errors in expectations.

Second, equation (4) shows that the NRU depends on markups (μ_0), labour market institutions ($\mathbf{X}_t$), and wage flexibility (α_1). Variations of models along the above NRU lines assert that generous unemployment benefits, increased union power, reduced product market competition, and low wage flexibility are responsible for a higher natural rate of unemployment. Note that in the NRU framework, growing variables - such as labour productivity, capital stock, and working age population - play no role in determining the long-run unemployment rate.

As already mentioned, despite the popularity of the NRU approach, several authors (e.g. Elhorst, 2003) have emphasised that regional unemployment disparities are the outcome of simultaneous employment, real wage, and labour force equations, rather than a single reduced form unemployment rate equation. Furthermore, much of the macro-labour research has established that a significant dimension in the state of unemployment is the lag structure that characterises the labour market system of affairs. Along these lines, the CRT argues that the labour demand/supply and wage setting lags interact with one another, and, thus, supports the use of dynamic multi-equation systems to determine the factors that drive unemployment.

2.2 CRT Models

In a framework of dynamic multi-equation models, the CRT views the movements in unemployment as the outcome of the responses of the endogenous variables to macro-labour "shocks" (i.e. changes in the exogenous variables). The 'chain reaction' epithet highlights the intertemporal responses of unemployment to shocks, propelled by interacting lagged adjustment processes. The latter refer to the lags of the endogenous variables in the system and are well documented in the literature.[4] For example, firms' current employment decisions commonly depend on their past employment on account of costs of hiring, training, and firing; current wage decisions depend on past wages due to staggered wage setting; labour force participation decisions depend on the past labour force on account of costs of entering and exiting from the labour force.[5] In turn, the network of lagged adjustments is generated by the spillovers that occur when endogenous variables have explanatory power in other equations of the system. We should point out that 'simultaneity', an issue inherent in CRT models, is being referred to as 'spillovers' to signify the plethora of feedback mechanisms, and flag the importance of the univariate representation of unemployment for the evaluation of the driving forces of unemployment.

We elaborate our analysis using a stylised labour market sysrem of labour demand, wage setting, and labour supply equations:

$$
\begin{aligned}
n_t &= \alpha_1 n_{t-1} + \beta_1 k_t - \gamma_1 w_t, && (5)\\
w_t &= \beta_2 x_t - \gamma_2 u_t, && (6)\\
l_t &= \alpha_2 l_{t-1} + \beta_3 z_t, && (7)
\end{aligned}
$$

where n_t, w_t and l_t are total employment, real wage, and labour force respectively; k_t denotes the capital stock, x_t is a wage-push variable (such as benefits or productivity), and z_t is the working age population; the autorregresive parameters α_1, α_2 are positive and satisfy the stability conditions ($|\alpha_i| < 1$, $i = 1, 2$); the β's and γ's are positive constants; all variables are in logs, and the error terms are ignored without loss of generality. In addition, we consider the log difference between labour force and employment as a close approximation of the unemployment rate (not in logs):

$$u_t = l_t - n_t. \qquad (8)$$

Observe that the autorregresive parameters α_1, α_2 are associated with the employment and labour force adjustment processes, respetively, and the γ's capture the spillover effects in the system. In particular, if $\gamma_1 = 0$ (zero wage elasticity) then shocks to the wage equation (changes in variable x) do not spillover to the employment equation and, thus, cannot affect unemployment. In other words, a significant wage elasticity of demand provides the mechanism through which changes in the wage push factor x feed through to unemployment. Moreover, if $\gamma_2 = 0$, i.e. unemployment does not put downward pressure on wages, changes in capital stock (k_t) and working-age population (z_t) do not have spillover effects, and so their influence

[4] See, among others, Nickell (1978), Taylor (1980), Lindbeck and Snower (1987), and Layard and Bean (1989).

[5] Of course, the employment, wage, and labour force adjustment processes may arise for reasons other than the ones given above.

on unemployment can be adequately measured by the individual labour demand (5) and supply (7) equations.

Let us rewrite the labour demand (5) and labour supply equations (7) as:

$$(1-\alpha_1 L)n_t = \beta_1 k_t - \gamma_1 w_t, \quad (9)$$
$$(1-\alpha_2 L)l_t = \beta_3 z_t, \quad (10)$$

where L is the lag operator. Substituting equation (6) into equation (9) gives:

$$(1-\alpha_1 L)n_t = \beta_1 k_t - \gamma\beta_2 x_t + \gamma_1\gamma_2 u_t. \quad (11)$$

Next, multiply both sides of equations (10) and (11) with the lag polynomials $(1-\alpha_1 L)$ and $(1-\alpha_2 L)$, respectively:

$$(1-\alpha_1 L)(1-\alpha_2 L)l_t = \beta_3(1-\alpha_1 L)z_t, \quad (12)$$
$$(1-\alpha_1 L)(1-\alpha_2 L)n_t = \beta_1(1-\alpha_2 L)k_t - \gamma_1\beta_2(1-\alpha_2 B)x_t + \gamma_1\gamma_2(1-\alpha_2 L)u_t. \quad (13)$$

Finally, we derive the univariate representation of unemloyment by using the definition (8) and subtracting equation (13) from equation (12):[6]

$$(1+\gamma_1\gamma_2-\alpha_1 L)(1-\alpha_2 L)u_t = \beta_3(1-\alpha_1 L)z_t - \beta_1(1-\alpha_2 L)k_t + \gamma_1\beta_2(1-\alpha_2 L)x_t. \quad (14)$$

Further algebraic manipulation of equation (14) gives:

$$u_t = \phi_1 u_{t-1} - \phi_2 u_{t-2} - \theta_k k_t + \theta_z z_t + \theta_x x_t + \alpha_2\theta_k k_{t-1} - \alpha_1\theta_z z_{t-1} - \alpha_2\theta_x x_{t-1}, \quad (15)$$

where $\phi_1 = \frac{\alpha_1+\alpha_2(1+\gamma_1\gamma_2)}{1+\gamma_1\gamma_2}$, $\phi_2 = \frac{\alpha_1\alpha_2}{1+\gamma_1\gamma_2}$, $\theta_k = \frac{\beta_1}{1+\gamma_1\gamma_2}$, $\theta_z = \frac{\beta_3}{1+\gamma_1\gamma_2}$ and $\theta_x = \frac{\gamma_1\beta_2}{1+\gamma_1\gamma_2}$.

In the light of equation (15), observe that the autoregresive parameters $\phi_1$and ϕ_2 result from the interactive dynamics within the labour market model, since they are a function of the employment and labour force adjustments, α_1 and α_2. The contemporaneous coefficients of the exogenous variables (θ's) embody the feedback mechanisms built in the system, since they are a function of the short-run sensitivities of the individual equations (β's) and the spillover effects (γ's). The fusion between lagged adjustment processes and spillover effects is emphasised by the lagged structure of the exogenous variables or, in time series jargon, "moving-average" terms.

Having derived the univariate unemployment representation (14) of our labour market model, we measure the corresponding natural rate, i.e., the equilibrium unemployment rate at which there is no tendency for this rate to change at any time t given the permanent component values of the exogenous variables at that time. In effect, the evaluated NRU, u_t^n, gives the unemployment rate as a function of the permanent components of the exogenous variables that

[6] Note that the above equation is dynamically stable, since (i) products of polynomials in L which satisfy the stability conditions are stable, and (ii) linear combinations of dynamically stable polynomials in L are also stable.

would prevail if the lagged adjustment processes had completed their course:

$$u_t^n = \frac{\beta_3(1-\alpha_1)z_t^p - \beta_1(1-\alpha_2)k_t^p + \gamma_1\beta_2(1-\alpha_2)x_t^p}{(1+\gamma_1\gamma_2-\alpha_1)(1-\alpha_2)}, \tag{16}$$

where the uppercase ^{p} indicates the permanent value of the exogenous variable. Note that this equation has been obtained by setting the lag operator equal to unity in equation (14).

2.3 Natural Rate and Frictional Growth

In what follows, we demonstrate the implications of the CRT for the long-run unemployment rate and the role of frictional growth in its determination. Recall that frictional growth arises from the interplay between lagged adjustment processes and growing variables in multi-equation models.

We start by making the plausible assumption that the exogenous variables in the labour market system (5)-(7) are growing with rates that stabilise in the long run and noting that, given definition (8), unemployment stabilises in the long run when

$$\Delta l^{LR} = \Delta n^{LR} = \lambda \quad \Leftrightarrow \quad \Delta u^{LR} = 0, \tag{17}$$

where the first difference $\Delta(\cdot)$ proxies the growth rate of the log variable and the superscript ^{LR} denotes its long-run value.

We then substitute the wage equation (6) into the labour demand equation (5), and rewrite the labour force (7) and labour demand (5) equations as

$$l_t = \frac{\beta_3}{1-\alpha_2}z_t - \frac{\alpha_2}{1-\alpha_2}\Delta l_t, \tag{18}$$

$$n_t = \frac{\beta_1}{1-\alpha_1}k_t - \frac{\gamma_1\beta_2}{1-\alpha_1}x_t + \frac{\gamma_1\gamma_2}{1-\alpha_1}u_t - \frac{\alpha_1}{1-\alpha_1}\Delta n_t. \tag{19}$$

Using the unemployment definition (8) and subtracting the latter equation from the former gives, after some algebraic manipulation, the following expresion for the unemployment rate:

$$\begin{aligned} u_t &= \xi\left(\frac{\beta_3}{1-\alpha_2}z_t - \frac{\beta_1}{1-\alpha_1}k_t + \frac{\gamma_1\beta_2}{1-\alpha_1}x_t\right) \\ &\quad +\xi\left(\frac{\alpha_1}{1-\alpha_1}\Delta n_t - \frac{\alpha_2}{1-\alpha_2}\Delta l_t\right), \end{aligned} \tag{20}$$

where $\xi = \frac{1-\alpha_1}{1-\alpha_1+\gamma_1\gamma_2}$.

Finally, we evaluate expresion (20) at the long-run values of the exogenous variables and use the stability restriction (17) to obtain:

$$u^{LR} = \xi\left[\underbrace{\left(\frac{\beta_3}{1-\alpha_2}z^{LR} - \frac{\beta_1}{1-\alpha_1}k^{LR} + \frac{\gamma_1\beta_2}{1-\alpha_1}x^{LR}\right)}_{\text{natural rate of unemployment}} + \underbrace{\frac{(\alpha_1-\alpha_2)\lambda}{(1-\alpha_1)(1-\alpha_2)}}_{\text{frictional growth}}\right]. \tag{21}$$

Observe that the long-run unemployment rate has effectively been decomposed into two components: the NRU and frictional growth.

Equation (21) provides useful insights with respect to the trajectory of the unemployment rate in the long run. Specifically, the long-run value $\left(u^{LR}\right)$ around which unemployment evolves reduces to the NRU only when frictional growth is zero. In other words, the NRU serves as an attractor of the actual unemployment rate eiher when the exogenous variables do not grow in the long run, i.e. $\lambda = 0$,[7] or when labour demand and supply share a common dynamic structure, i.e. $\alpha_1 = \alpha_2$. Given that neither of these two conditions seems plausible, disregarding the phenomenon of frictional growth in the evolution of unemployment implies that the NRU testament may lead to erroneous policy responses.

With the chain reaction framework of analysis in the background, we carry on to investigate the large and persistent regional unemployment disparities in Spain. We first examine the magnitude and dynamics of these disparities, and then challenge the conventional NRU view by estimating a CRT labour market model, and assesing the role played by frictional growth in the long-run unemployment rates.

3 Regional Unemployment Disparities

In their influential work for the US, Blanchard and Katz (1992) show that regional unemployment disparities are not persistent as a result of high labour and firm mobility: workers move from high to low unemployment regions in search for better labour market prospects, while firms move to high unemployment regions to benefit from lower labour costs.[8] It is, thus, not surprising that this contribution had a profound impact on the regional labour market literature (see, inter alia, Decressin and Fatas, 1995; Jimeno and Bentolila, 1998; Fredriksson, 1999; and Elhorst, 2003). Nevertheless, by relying on perfect labour mobility and focusing exclusively on idiosyncratic shocks, the Blanchard and Katz model has been open to criticism. Bartik (1993) and Rowthorn and Glyn (2006) show that the Blanchard and Katz results are exposed to the small sample bias inherent in short time series data, and the large measurement errors in survey based series of employment status at the state level. Correcting for these biases, these papers find no support for the assumption of a highly flexible regional labour market in the US. Regarding the evolution of Spanish unemployment, Bande et al. (2007, 2008) show that regional disparities are affected by strong imitation effects in the wage bargaining process. Bande and Karanassou (2009) identify two groups of Spanish regions, and demonstrate that the increase in unemployment rate disparities is the outcome of the different adjustments of each group to region-specific and national shocks.

[7] Note that the restriction (17) can be writen in terms of the growth rates of the exogenous variables:

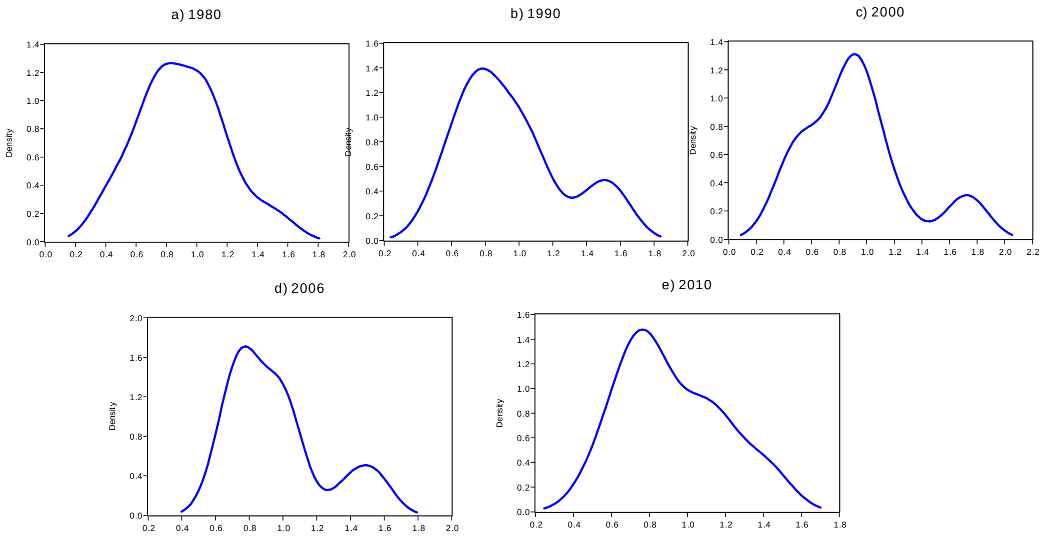
$$\frac{\beta_1}{1-\alpha_1}\Delta k^{LR} - \frac{\gamma_1\beta_2}{1-\alpha_1}\Delta x^{LR} = \frac{\beta_3}{1-\alpha_2}\Delta z^{LR} = \lambda.$$

[8] This is because the large fraction of unemployed workers puts downward pressure on wages.

3.1 Kernel Analysis: Changes in the Disparities

We analyse the regional unemployment distribution in Spain by estimating kernel density functions of the relative unemployment rates.[9] In particular, the kernel density estimator employed here follows the work of Quah (1997), Overman and Puga (2003), and López-Bazo et al. (2002, 2005).[10] Using regional unemployment data from the Spanish Labour Force Survey (EPA), we estimate the kernel density at different points in time and evaluate the shape of the distribution.[11] Results are portrayed in Figure 1.

Figure 1. Kernel density functions. Relative unemployment rates



Notes: all densities have been estimated w ith a gaussian kernel.
For the bandw ith the Silverman option has ben chosen

Panel a) of Figure 1 plots the estimated distribution in 1980. We clearly observe that regional unemployment rates were almost normally distributed around the aggregate unemployment rate (as the mean/mode of relative unemployment rate is close to unity), but a two-mode distribution

[9] Relative unemployment rates are defined as the ratio of regional over national unemployment rates. See Martin (1997) for a detailed discussion regarding the usefulness of absolute and relative disparities measures.

[10] A kernel function is defined as

$$\int_{x=-\infty}^{x=+\infty} K(u)du = 1.$$

A class of density estimators (the Ronsenblatt-Parzen Kernel density estimators) can be defined as

$$\widehat{f}_K = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right),$$

where the function K refers to the Kernel function, n is the number of observations in the sample and h is the bandwidth. For the function K in our estimations we use the Gaussian Kernel, while the bandwidth is chosen according to the Silverman option, such that $h = 0.9n - \frac{1}{5}min(s, \frac{R}{1.34})$, where n is the number of observations, s is the standard deviation and R is the interquartile range of the series (Silverman, 1986).

[11] The regional unemployment data from the Spanish Labour Force Survey (EPA) are homogeneous from 1980 to 2005. To analyse the distribution during the Great Recession we also use data from 2006 to 2010. Sinse the Labour Force Survey experienced a major redesign in 2005, the post-2005 unemployment series are not fully comparable to data from the previous years.

is starting to appear. By 1990 a two-regime distribution has been well established (Figures 1b-c). The kernel density in 1990 (2000) is clearly characterised by two modes: a low unemployment regime located around 0.8 (0.9) and a high unemployment one around 1.6 (1.8). In fact, the plots demonstrate that the high economic growth experienced by the Spanish economy since 1995 was associated with an intensified divergence of regional unemployment rates (Bande et al., 2008, explain the larger disparities during boom phases on the basis of the influence of the wage bargaining process). The abrubt arrival of the Great Recession put the brakes on the divergent evolution of regional unemployment rates. The surprising increase in unemployment (by 2011 Spain recorded around 5 million unemployed workers, and an aggregate unemployment rate of 21%) brought about a drastic reduction in disparities. Panel e) of Figure 1 shows that the distribution of regional unemployment in 2010 was located around the Spanish national rate, even though two modes can still be slightly depicted (at 0.7 and 1.2, respectively).

3.2 Cluster Analysis: Who is Who?

In the light of the kernel density evidence that Spain is characterised by two large groups of regions in terms of their unemployment rates, we conduct a cluster analysis to identify which regions belong to each group (see Everitt *et al.*, 2001, for different examples of cluster analysis). Exogenous regional data are used to determine the group members: those regions that have increased their relative unemployment rate throughout the sample form the high unemployment group, while those that have improved their relative position form the low unemployment group. The classification criteria have been designed according to the regional participation rate, the regional relative per capita income level and the regional relative unemployment rate.[12]

The cluster analysis classification results are shown in Table 1. We should point out that this classification is almost identical to Bande and Karanassou (2009), where he relative unemployment was the only grouping classification variable and the sample was shorter (1980-1995). The only difference is that Pais Vasco has now been identified as a region in the low unemployment group.[13]. As expected, the first group is characterised by large relative unemployment rates, lower relative per capita income levels and low participation rates. By contrast the second group is characterised by low unemployment, high per capita income levels and higher participation rates.

[12] Our aim is not to group regions according to the performance of their unemployment rate alone (this would yield an endogenous classification), but rather to group them as a function of socio-economic features that have an influence on such unemployment performance. Justification for the choice of these additional variables can be found in Bande *et al.* (2008).

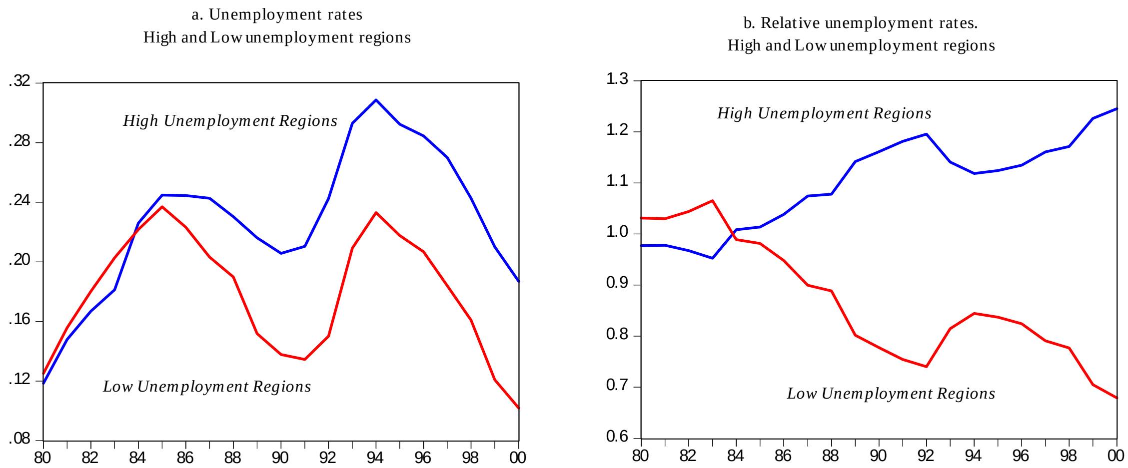
[13] Detailed results on the cluster analysis are available upon request.

Table 1: Cluster Analysis

High unemployment regions			Low unemployment regions		
Andalucia			Aragón		
Asturias			Baleares		
Canarias			Cataluña		
Cantabria			Madrid		
Castilla-La Mancha			Navarra		
Castilla y León			País Vasco		
Extremadura			La Rioja		
Galicia					
Murcia					
Comunidad Valenciana					
	Mean	Std. Dev.		Mean	Std. Dev.
Activity Rate	0.518	0.03	Activity Rate	0.539	0.03
Rel. p.c. income	0.856	0.09	Rel. p.c. income	1.209	0.06
Rel.unempl. rate	1.149	0.346	Rel.unempl. rate	0.655	0.208
Notes: Std. Dev. is the standard deviation.					

Figure 2a plots the absolute unemployment rates of each group, while Figure 2b shows that the contrast in their evolution through time is reflected by the dramatic increase in the disparities between the relative unemployment rates of the two groups. Observe that there has been a sustained increase (decrease) in the relative unemployment rate of the group of high (low) unemployment since 1983, the only exception being the 1992-1994 period when it briefly decreased (increased). Also, note that during the recession in the beginning of the eighties, the high unemployment group was in fact a 'low unemployment' group, with its classification status being ammended in 1984.

Figure 2. Unemployment rates and relative unemployment rates



Moreover, the counter cyclical behaviour of regional unemployment disparities is evident in the graph: during booming years (1985-1991 and 1994-2000) the distance between the relative unemployment rates of the high and low groups increases markedly, while during recessions (1980-1984 and 1992-1993) the distance is reduced. This behaviour is characteristic of the Spanish regional labour market. Bande et al. (2008) find that the booming period of 1985-1991 was accompanied by a decentralisation of the wage bargaining system (which was highly centralised and coordinated) gave rise to an important imitation effect. This effect allowed the less productive sectors in the less productive regions to link their wage growth to the conditions prevailing in the most productive sectors in the most productive regions, thus, increasing unit labour costs and limiting the ability to create employment during economic upturns.

Bande and Karanassou (2009) find that this evolution of disparities may be explained by a combination of i) different feedback mechanisms generating different unemployment responses even when regions face common shocks, and ii) different degrees of labour market flexibility that result from the mix of lagged edjustment processes and region-specific shocks. They find that during good times high unemployment regions do not benefit as much (in terms of unemployment reduction) as low unemployment regions, while during bad times exactly the reverse holds. This explains why regional disparities in Spain show a marked counter cyclical pattern, which is not present in other European countries.

The existence of a high and low unemployment group of regions with distinct economic performaces forms the basis of the empirical approach in the next section, where we estimate idiosyncratic regional labour market models for each group and show that there are substantial differences bewteen the two labour markets.

4 Econometric Methodology

Working with two panels of regions, one panel of the ten high unemployment rate regions and another one of the seven low unemployment rate regions, we estimate an expanded version of the structural chain reaction model presented in Section 2. In paricular, our empirical labour demand, wage setting and labour force equations are characterised by a variety of lagged adjustment processes and feedback mechanisms.

4.1 Model Outline

We explain unemployment rate disparities by estimating each behavioural equation of our labour market chain reaction model by an autoregressive distributed lag (ARDL) approach. We can express the structural vector ARDL system of equations for the Spanish regions as follows:[14]

$$\mathbf{A}_0\mathbf{y}_{it} = \mathbf{A}_1\mathbf{y}_{i,t-1} + \mathbf{A}_2\mathbf{y}_{i,t-2} + \mathbf{B}_0\mathbf{x}_{it} + \mathbf{B}_1\mathbf{x}_{i,t-1} + \mathbf{C}_0\mathbf{z}_t + \mathbf{C}_1\mathbf{z}_{t-1} + \mathbf{e}_{it}, \tag{22}$$

[14] The dynamic system (22) is stable if, for given values of the exogenous variables, all the roots of the determinantal equation

$$\left|\mathbf{A}_0 - \mathbf{A}_1 L - \mathbf{A}_2 L^2\right| = 0$$

lie outside the unit circle. Note that the estimated equations below satisfy this condition.

where y_{it} is a vector of endogenous variables, x_{it} is a vector of regional exogenous variables, z_t is a vector of national exogenous variables, the A's, B's and C's are coefficient matrices, and e_{it} is a vector of error terms.

Estimation of the above structural system (22) involves the selection of the exogenous variables and the number of lags to be included in each of its equations. As these are mainly judgemental decisions, the methodology of structural modelling relies heavily on discretion. Nevertheless, the advantage of the structural modelling approach is the economic intuition and plausibility that accompanies each of the estimated equations.[15]

Acknowledging the need for a large number of observations for a robust investigation of the evolution of regional unemployment disparities through time, we opt for pooled estimation.[16] Specifically, we use a fixed-effects (FE) model comprising the system (22) and a vector of one-way error component disturbances ($\mathbf{e}_{it}$):

$$\mathbf{e}_{it} = \boldsymbol{\mu}_i + \mathbf{v}_{it},\ i = 1, ..., N,\ t = 1, ..., T, \tag{23}$$

where $v_{it} \sim iid\left(\mathbf{0}, \boldsymbol{\sigma}_{\nu}^2\right)$ with $Cov\left(\mathbf{e}_{it}, \mathbf{e}_{jt}\right) = 0$, for $i \neq j$. The vector of scalars μ_i represents the effects that are specific to the ith region and are assumed to remain constant over time. In other words, the FE model assumes that slope coefficients and variances are identical across regions and only intercepts are allowed to vary.

Due to data limitations, our dataset covers the 1980-2000 period,[17] and is obtained from (i) Datastream, (ii) the BD-MORES dataset, elaborated by the Dirección General de Análisis y Programación Presupuestaria (Ministry of Economy) and the University of Valencia, and (iii) the Spanish Labour Force, elaborated by the Spanish Statistics Institute (INE). FE estimation enables us to use 210 and 147 observations for the high and low unemployment rate panels, respectively. The variables are defined in Table 2.

The multi-equation system (22) consists of (i) a labour demand equation, describing the equilibrium employment (n_{it}), (ii) a wage setting equation, describing real wage (w_{it}) determination, and (iii) a labour supply equation, describing the equilibrium size of the labour force (l_{it}). In addition, our model contains the definition of the unemployment rate (8): $u_{it} = l_{it} - n_{it}$. According to (22) the regional unemployment rate is determined by (i) local conditions measured by the regional exogenous variables x_{it} (such as capital stock), and (ii) nationwide variables z_t (such as oil prices) which are common to all regions. In contrast, the models in Blanchard and Katz (1992), and Decressin and Fatás (1995) emphasise regional dynamics as opposed to national dynamics, analysing exclusively the effects of regional specific shocks.

[15] See Karanassou and Sala (2010) for a detalied discussion and comparison of the simultaneous equations, (structural) VAR, and CRT econometric methodologies.

[16] The advantages of using panel data sets for economic research are numerous and well documented in the literature. See, for example, Hsiao (1986) and Baltagi (2008) for a detailed exposition of stationary panel data estimation.

[17] The reason for restricting our analysis to the 1980-2000 period is twofold. First, the regional capital stock series is obtained from the BD-MORES dataset which currently covers the 1980-2000 period (see Dabán *et al.*,2002, for a detailed description). The second is the methodological change in the Labour Force Survey in 2002 and 2005.

Table 2: Definitions of Variables

Regional variables		National variables	
n_{it} :	total employment	oil_t :	real oil price
l_{it} :	labour force	b_t :	real social security benefits per person
u_{it} :	unemployment rate $(= l_{it} - n_{it})$	tax_t :	direct tax rate (as a % of GDP)
w_{it} :	real wage (=labour income per employee)		
k_{it} :	real capital stock		
pop_{it} :	working age population		
pr_{it} :	real productivity		

Notes: all variables are in logs except for the unemployment rate, u_{it}, real social security benefits, b_t, and the direct tax rate, tax_t.

Each panel of regions is modeled along the lines of the structural system (22). Our model does not account for any labour or firm mobility between the high and low unemployment groups of regions.

Each panel of regions is modeled along the lines of the structural system (22). Our model does not account for any labour or firm mobility between the high and low unemployment groups of regions.[18] This is in line with the results for Europe by Decressin and Fatás (1995) but is in contrast to the findings of Blanchard and Katz (1992) who assume perfect mobility of workers and firms between regions, and find that this assumption is valid for the behaviour of US workers and firms.

Dynamic panel data and nonstationary panel time series models have attracted a lot of attention over the past several years. As a result, the study of the asymptotics of macro panels with large N (number of units, e.g. countries or regions) and large T (length of the time series) has become the focus of panel data econometrics.[19] Thus, we carry on with unit root tests to decide whether or not to use stationary panel data estimation techniques.

4.1.1 Unit Roots Tests

In particular, we test the order of integration of the national variables using the KPSS unit root test.[20] Table 3 presents these tests and shows that for all four national variables - real oil price, real social security benefits, direct tax rate, and trade deficit - we cannot reject the null hypothesis of (trend) stationarity.

Table 3: Unit Root Tests

	oil_t	b_t	tax_t	$trade_t$	5% c.v.
KPSS_c	0.48	0.31	0.45	0.09	0.46
$\text{KPSS}_{c,t}$	0.17	0.11	0.15	0.06	0.15

KPSS_c uses an intercept in the test.

$\text{KPSS}_{c,t}$ uses an intercept and trend in the test.

[18] Reasons for the convenience of this type of modelling can be found in Bande and Karanassou (2009, 2010)

[19] Banerjee (1999) and Baltagi and Kao (2000), and Smith (2000) provide an overview of the above topics and survey the developments in this technical and rapidly growing literature.

[20] See Kwiatkowski, Phillips, Schmidt and Shin (1992) for details.

Since it is widely accepted that the use of pooled cross-section and time series data can generate more powerful unit root tests,[21] we examine the stationarity of the regional variables using panel unit root tests. We apply the simple statistic proposed by Maddala and Wu (1999) - this is an exact nonparametric test based on Fisher (1932):

$$\lambda = -2\sum_{i=1}^{N} \ln p_i \sim \chi^2 (2N), \tag{24}$$

where p_i is the probability value of the ADF unit root test for the ith unit (region). The Fisher test has the following attractive characteristics. First, since it combines the significance of N different independent unit root statistics, it does not restrict the autoregressive parameter to be homogeneous across i under the alternative of stationarity. Second, the choice of the lag length and of the inclusion of a time trend in the individual ADF regressions can be determined separately for each region. Third, the sample sizes of the individual ADF tests can differ according to data availability for each cross-section. Finally, it should be noted that the Fisher statistic can be used with any type of unit root test. Maddala and Wu (1999), using Monte Carlo simulations, conclude that the Fisher test outperforms both the Levin and Lin (1993) and the Im, Pesaran and Shin (2003) tests.

Table 4 reports the Fisher statistics for all the variables used in our structural equations. The null hypothesis is that the time series has been generated by an $I(1)$ stochastic process, and the test follows a chi-square distribution with 34 degrees of freedom (the 5% critical value is 48.32). Note that all the panel unit root test statistics are greater than the critical value, so the null of a unit root can be rejected at the 5% significance level.

Table 4: Panel Unit Root Tests

$\lambda(n_{it})$	=	65.26	$\lambda(w_{it})$	=	49.10	$\lambda(pop_{it})$	=	51.94
$\lambda(l_{it})$	=	55.94	$\lambda(k_{it})$	=	82.80	$\lambda(pr_{it})$	=	49.08

Notes: $\lambda(\cdot)$ is the test proposed by Maddala and Wu (1999).
The test follows a chi-square (34) distribution.
The 5% critical value is approximately 48.

Tables 3 and 4 indicate that it is appropriate to apply stationary panel data estimation techniques.

4.1.2 Estimation Issues

The estimation of a model of the type of (23) involves a number of interesting and important issues related to the dynamic structure impossed on it. In order to clarify these issues let us discuss them along the lines of a very simple dynamic panel data model.[22] Consider an ARDL

[21] See, for example, Levin and Lin (LL) (1993), Im, Pesaran and Shin (2003), Harris and Tzavalis (1999), Maddala and Wu (1999). Note that the asymptotic properties of tests and estimators proposed for nonstationary panels depend on how N (the number of cross-section units) and T (the length of the time series) tend to infinity, see Phillips and Moon (1999).

[22] Here we follow Smith and Fuertes (2010).

(1,0) panel model with homogenous slopes but differing constants:

$$y_{i,t} = \alpha_i + \beta x_{i,t} + \gamma y_{i,t-1} + u_{i,t}, \quad u_{it} \sim i.i.d.N(0, \sigma^2),$$

where the independence assumption for the error terms refers to time and cross-section, i.e., $E(u_{i,t}u_{j,t-s}) = 0$ for $i \neq j$ or $s \neq 0$. The FE estimator (also known as the least squares dummy variables, LSDV, estimator, or the within-group, or the analysis of covariance estimator) is the most common estimator for dynamic panels. In homogenous dynamic panels (i.e. models with constant slopes) the FE estimator is consistent as $T \to \infty$, for fixed N.[23]

However, the LSDV estimator provides inconsistent estimates of the mean effects β and γ when $N \to \infty$ for a fixed T. This is usually called the Nickell bias and is the result of the fact that for a fixed T the lagged dependent variable bias arising from the initial conditions is not removed, even when $N \to \infty$ (Nickell, 1981). Bun and Kiviet (2003) discuss the size of the bias in balanced panels. If both $T \to \infty$ and $N \to \infty$, then to ensure consistency of the least squares estimates T must grow sufficiently fast relative to N, such that $N/T \to \kappa$, where $0 \leq \kappa < \infty$ (Alvarez and Arellano, 2003).

Therefore, when T is small relative to N the OLS estimation is clearly inconsistent. In this case the standard approach is to use a General Method of Moments (GMM) estimator, such as the Arellano and Bond (1991) DPD or the Blundell and Bond (1998) BB estimators. In this tradition the data is first differenced in order to eliminate the fixed effects. This, in turn, induces a correlation between the differenced error and the right-hand side variables that is dealt with by GMM. On one hand, the problem that the traditional GMM estimator works very badly when the variables are I(1) does not apply to our analysis, given the results of the unit root tests. On the other, it is well known that the GMM estimator is efficient for large cross sections with relative few time periods (Baltagi, 2008).

We can thus argue that our empirical model is not likey to be affected by the Nickell bias, since for each group of regions the time dimension is clearly greater than the cross-section dimension: the high unemployment group forms a panel with 21 time observations $\times$ 10 regions, whereas the low unemployment group forms a panel of 21 $\times$ 7. In other words, N/T is rather small (0.47 and 0.33, respectively) so that we can confidently assume that T grows sufficiently fast relative to N. Furthermore, since GMM requires first differencing of the variables to eliminate fixed effects, application of this procedure would not allow us to achieve our main objectine, i.e to estimate the natural rate of unemployment for each group of regions. This is because the lack of fixed effects would leave us with an indeterminancy of the fitted values level of employment, wage, and labour force for each region.

In this light, we are justified to proceed with the standard one-way fixed effects estimation. Nevertheless, we have also estimated the individual equations of our model by the Arellano and Bond DPD estimator and compared the results with the OLS case. (The results of these auxiliary estimations are summarised in Tables A1-A2 in the Appendix.) Interestingly, the

[23] Kiviet (1995) showed that the bias of the FE estimator in a dynamic model of panel data has an approximation error of $O\left(N^{-1}T^{-3/2}\right)$. Therefore, the FE estimator is consistent only as $T \to \infty$, while it is biased and inconsistent when N is large and T is fixed.

estimates in all equations are similar between the two methods. This finding reinforces our point that the Nickell bias does not represent an issue in our regional context, and confirms the validity of the $LSDV$ estimator.

4.2 Estimation Results

The fixed effects estimated models of high and low unemployment groups of regions are presented in Tables 5 and 6, respectively. These were preferred to the heterogeneous models of individual (regional) time series regressions, according to the Schwarz model selection criterion.[24] Recall that FE estimation implies that regions within a specific group share identical coefficients for the explanatory variables, while differences in labour market behaviour across regions is captured solely through fixed effects (i.e. differing constants in the estimated equations).[25]

Regarding labour demand, the lagged employment terms are associated with the *employment adjustment* process. Employment depends negatively on the real wage, and positively on both the level and growth rate of capital stock. The oil price and direct taxes (as a ratio to GDP) have a negative impact on labour demand.

In the wage setting equation, real wage depends negatively on unemployment and the trade deficit, and positively on productivity and benefits. The lag of real wage reflects the adjustment process due to *wage staggering.*

Finally, concerning labour supply, the autoregressive coefficient signifies the influence of the *labour force adjustment* process, and the size of the labour force depends positively on working age population and negatively on real wages.[26] Also note that, in each equation of each group, all variables are statistically significant at conventional levels.

It is worthwhile to observe that in the above estimations the unemployment rate is influenced by the size of the capital stock both in the short run and long run. This is a key characteristic of the CRT, which, unlike the influential NRU, asserts that trended factors (such as capital stock and working age population) influence the trajectory of the unemployment rate, a non trended variable.

Given the panels of equations in Tables 5-6, this crucial point can be justified by arguing that each equation in the labour market model is balanced (dynamically stable) so that each trended endogenous variable is driven by the set of its trended determinants. More importantly, it can be shown that the implied univariate representation of the unemployment rate is also balanced, as

[24] Specifically, we select between each of the pooled equations presented in Tables 5 and 6 and the corresponding individual regressions by using the Schwarz Information Criterion (SIC). We compute the model selection criteria as follows:

$$\begin{aligned} SIC_{pooled} &= MLL - 0.5k_{pooled}\log(NT), \\ SIC_{individual} &= \sum_{i=1}^{j} MLL_i - N\left[0.5k_i \log(T)\right], \ j = 11, 6 \end{aligned}$$

where MLL_{pooled}, MLL_i denote the maximum log likelihoods of the pooled model and the ith region time series regression, respectively; k_{pooled}, k_i are the number of parameters estimated in the fixed effects model and the individual region time series regression, respectively; N is the number of regions and T is the time dimension of the sample size. The model that maximises SIC is preferred. (Results are available upon request.)

[25] Results on the fixed effects of the regions (the estimated regional constants) are available upon request.

[26] The negative impact of the real wage indicates that the income effect dominates.

equilibrating mechanisms in the labour market and other markets jointly act to ensure that the unemployment rate is trendless in the long run (Karanassou and Snower, 2004). In particular, restrictions on the relationships between the long-run growth rates (as opposed to the levels) of capital stock and other growing exogenous variables are sufficient for this purpose.[27]

Table 5: High Unemployment Group of Regions

Labour demand: n_{it}			Wage setting: w_{it}			Labour supply: l_{it}		
	coef.	p-value		coef.	p-value.		coef.	p-value
$n_{i,t-1}$	0.69	0.00	$w_{i,t-1}$	0.62	0.00	$l_{i,t-1}$	0.78	0.00
	(0.03)			(0.04)			(0.04)	
$w_{i,t}$	-0.30	0.00	u_{it}	0.49	0.00	w_{it}	-0.05	0.00
	(0.04)			(0.08)			(0.01)	
$k_{i,t}$	0.30	0.00	$u_{i,t-1}$	-0.61	0.00	pop_{it}	0.34	0.00
	(0.03)			(0.09)			(0.06)	
$\Delta k_{i,t}$	1.14	0.00	pr_{it}	0.20	0.00	Δpop_{it}	0.54	0.01
	(0.22)			(0.04)			(0.22)	
oil_t	-0.01	0.04	b_t	0.22	0.00			
	(0.006)			(0.05)				
tax_t	-0.56	0.06						
	(0.30)							
MLL=468.33			MLL=432.17			MLL=566.65		
S.I.C.=-4.25			S.I.C=-3.92			S.I.C.=-5.29		

OLS estimation. Standard errors in parentheses; Δ denotes the difference operator.
MLL is the maximum log likelihood; S.I.C. is the Schwarz information criterion.
Regions included: AND, AST, CAN, CANT, CLM, CYL. EXT, GAL, MUR, VAL

Table 6: Low Unemployment Group of Regions

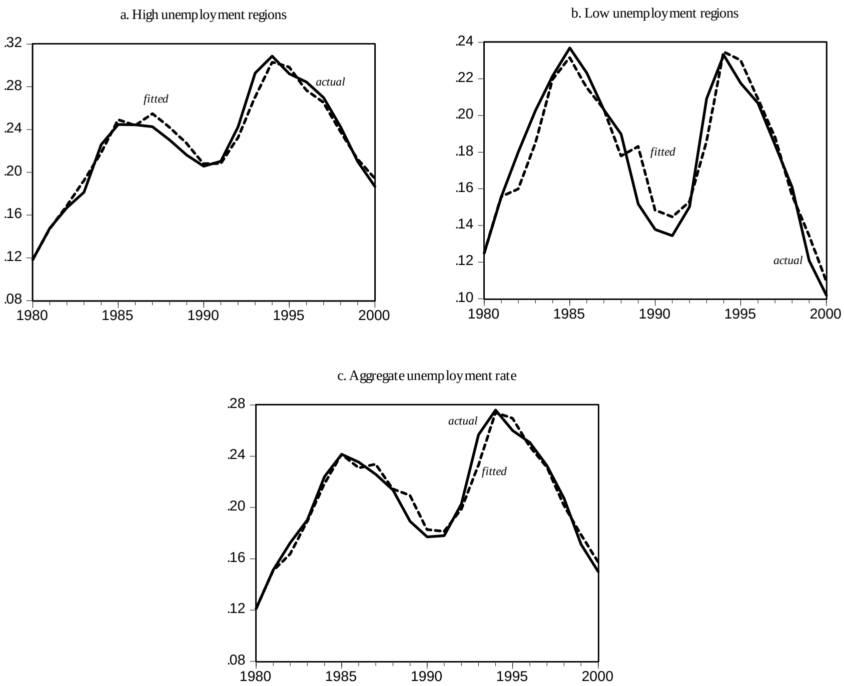
Labour demand: Δn_{it}			Wage setting: w_{it}			Labour supply: l_{it}		
	coef.	p-value		coef.	p-value.		coef.	p-value
$n_{i,t-2}$	-0.35	0.00	$w_{i,t-1}$	0.50	0.00	$l_{i,t-1}$	0.68	0.00
	(0.04)			(0.05)			(0.06)	
$w_{i,t}$	-0.16	0.00	$u_{i,t}$	0.27	0.00	$w_{i,t}$	-0.10	0.01
	(0.04)			(0.09)			(0.04)	
$k_{i,t}$	0.26	0.00	$u_{i,t-1}$	-0.33	0.00	$w_{i,t-1}$	0.09	0.02
	(0.03)			(0.10)			(0.04)	
$\Delta k_{i,t}$	0.82	0.00	pr_{it}	0.29	0.00	$pop_{i,t}$	0.48	0.00
	(0.19)			(0.06)			(0.09)	
oil_t	-0.02	0.00	b_t	0.27	0.00	$\Delta pop_{i,t}$	0.51	0.07
	(0.007)			(0.07)			(0.28)	
tax_t	-1.15	0.00						
	(0.30)							
MLL=333.74			MLL=320.87			MLL=395.71		
S.I.C.=-4.54			S.I.C.=-4.16			S.I.C.=-5.22		

OLS estimation. Standard errors in parentheses; Δ denotes the difference operator.
MLL is the maximum log likelihood; S.I.C. is the Schwarz information criterion.
Regions included: ARA, BAL, CAT, MAD, NAV, PV, RIO

[27] See Bande and Karanassou (2010) for a detailed account of the role of capital acummulation on the evolution of Spanish regional unemployment.

Figure 3 shows that the fitted unemployment rate generated by our system tracks the trajectory of the actual unemployment rate very closely.

Figure 3. Actual and fitted values



5 Actual and Natural Rates of Unemployment

On the basis of the empirical results in Tables 5-6, this section attempts to evaluate the natural rates of unemployment in each group of regions and compare their evolution through time.

In this respect, we compute the unemployment rate according to equation (16), i.e. the unemployment rate that would prevail had the dynamics fully worked themselves out at any time t, given the permanent values of the exogenous variables in the model. To achieve this we (i) consider the steady-states of the equations in the estimated panels of Tables 5 and 6 (i.e. we set the lag operators equal to unity), and (ii) identify the permanent components of the exogenous variables by estimating kernel density functions, a procedure proposed by Karanassou et al (2008). Note that this method is an alternative to extracting the permanent components of a time series using the Hodrick-Prescott filter, Kalman filter, etc.

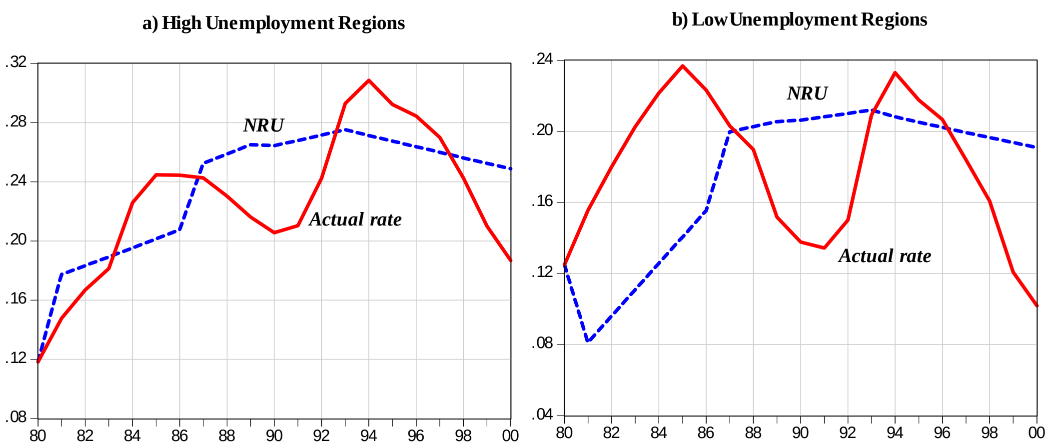
Plotting the kernel density distribution of each stationary exogenous variable is indicative of the number and status of the different regimes present in the series. A unimodal density characterises a unique regime, which is regarded as permanent in our sample period and its mean is equal to the value of the mode. A bimodal kernel density describes the case of two regimes divided by a "valley point": the boundaries of the two regimes depend on whether observations lie to the left or to the right of this data point.

When a series exhibits two regimes we compare its kernel density with the actual series. If a variable starts in a regime (say A) in the beginning of the sample and then moves to another regime (say B), we need to observe whether this change is permanent or transitory. If the variable returns to regime A, then regime B is transitory and A is permanent, measured by the corresponding mode value. However, if the variable remains at regime B, then the latter is regarded as another permanent regime. For a nonstationary variable (for instance, capital stock), we compute the kernel density function of its growth rate, identify the regime of this growth variable, and then compute the associated level of its permanent component series.[28]

Having identified the permanent and temporary regimes, we substitute the permanent components series of the exogenous variables in the equations of Tables 5-6, set the lagged values equal to the current ones (i.e. the lag operator $L = 1$), and solve the resulting models for the unemployment rate to obtain the natural rate of each region. The NRU of each group is computed by summing up the regional natural levels of employment and labour force, and then subtracting these summations according to the unemployment definition (8).

The results are pictured in Figure 4. Panels a) and b) plot the actual and natural rates of the high and low unemployment groups of regions, respectively.

Figure 4. Actual and Natural Rates of Unemployment.
High and Low unemployment regions



The information in Figure 4 provides some interesting insights regarding the evolution of the NRU and the actual rates. Starting with the first half of the eighties, actual unemployment deviated markedly (almost 4-8 percentage points, pp) from its natural rate. More importantly, note that, while the strong economic recovery of the second half of the eighties led to a substantial reduction in the actual unemployment rates (about 4 pp in the high unemployment group, and 12 pp in the low unemployment regions), this was not accompanied by a decrease in the natural rates. In contrast, the NRUs continued increasing, reaching their highest levels during the recession of the early nineties, and then slightly decreased by 2000. As the actual unemployment

[28] To conserve space, we do not report these calculations as they involve seventeen regions, three exogenous regional variables and three exogenous national variables. Results are available upon request from the authors.

rate had experienced a large fall of more than 10 pp from its peak in the mid 1990s, the NRU was 11 (7) pp higher than the actual rate in the low (high) unemployment group of regions in 2000.

These results clearly show that unemployment has not evolved around its natural rate over the 1980-2000 period. Put differently, the NRU has not acted as an attractor of the regional unemployment in Spain.[29]

6 Conclusions

The Spanish unemployment problem, among the worst in the European Union during the past decades, has been further aggravated by the dramatic increase in the degree of its regional unemployment disparities.

The standard approach to explaining regional unemployment disparities asserts that the differences in regional natural rates (due to ammenities, composition of the labour force, different labour market institutions, etc.) are responsible for the existence of large unemployment disparities across regions. Since the NRU viewpoint states that actual unemployment evolves around its natural rate, the policy implications are that supply-side measures should be implemented in order to reduce the negative effects of institutions and shocks on regional unemployment.

This paper, following the chain reaction approach, demonstrated that unemployment does not gravitate towards its natural rate as a result of the phenomenon of frictional growth, namely the interplay of lagged adjustment processes and growth in the labour markets. Consequently, we can argue that the NRU explanation of regional disparities is misleading.

The analysis in Section 2 showed that, unlike the single-equation NRU models, the CRT multi-equation systems are characterised by a network of interacting lagged adjustment processes, and include growing variables in their explanatory sets. Thus, a CRT framework views the movements in unemployment as ‘chain reactions’ (intertemporal responses) to labour market shocks, and can capture frictional growth. Since different regions may be exposed to different types of shocks and experience different lagged adjustment processes, CRT models have a clear advantage over NRU ones in explaining regional unemployment disparities.

The Spanish regions were classified in Section 3 into two categories, one group with high unemployment rates and another with low unemployment rates. In Section 4 we used a regionally adapted version of the CRT model, analysed in Section 2, to examine the evolution of regional unemployment in Spain during the period 1980-2000. Subsequently, in Section 5, we computed the natural rates corresponding to the estimated labour market models for each group. According to our findings, the deviations of actual unemployment from its natural rate are substantial throughout the sample, indicating that frictional growth is an important factor in the evolution of regional unemployment disparities.

These results imply that policies aiming at reducing disparities by reducing the natural rates

[29] A standard regresion of the actual unemployment rate on the natural rate shows that for the high unemployment group of regions the natural rate accounts for 53% of the total variation of the actual rate if we take the whole sample, and only 6% if we consider the period from 1986 to 2000. For the low unemployment group of regions these figures would be of only 0.2% and 2% respectively.

are likely to fail, since these do not take into account the element of frictional growth (arising from the interplay of labour market flexibility and changes in investment, productivity, etc.) in the evolution of regional unemployment. Furthermore, it can be argued that different policies should be applied to different groups of regions, a result that casts doubts on the effectiveness of the recent policy decisions by the Spanish government to apply a common set of labour market reforms to the whole country.

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Appendix

Table A1: High unemployment group of regions. OLS and GMM estimation.

Labour demand: n_{it}					Wage setting: w_{it}					Labour supply: l_{it}				
	OLS		GMM			OLS		GMM			OLS		GMM	
	coef.	p-value	coef.	p-value		coef.	p-value	coef.	p-value		coef.	p-value	coef.	p-value
$n_{i,t-1}$	0.69 (0.03)	0.00	0.68 (0.03)	0.00	$w_{i,t-1}$	0.62 (0.04)	0.00	0.47 (0.05)	0.00	$l_{i,t-1}$	0.78 (0.04)	0.00	0.72 (0.04)	0.00
$w_{i,t}$	−0.30 (0.04)	0.00	−0.33 (0.03)	0.00	u_{it}	0.49 (0.08)	0.00	0.42 (0.07)	0.00	w_{it}	−0.05 (0.01)	0.00	−0.08 (0.01)	0.00
$k_{i,t}$	1.45 (0.22)	0.00	1.66 (0.20)	0.00	$u_{i,t-1}$	−0.61 (0.09)	0.00	−0.47 (0.07)	0.00	pop_{it}	0.89 (0.21)	0.00	0.99 (0.20)	0.00
$k_{i,t-1}$	−1.14 (0.22)	0.00	−1.34 (0.20)	0.00	pr_{it}	0.20 (0.04)	0.00	0.20 (0.04)	0.00	pop_{it-1}	−0.54 (0.22)	0.02	−0.53 (0.21)	0.01
oil_t	−0.01 (0.006)	0.04	−0.01 (0.005)	0.00	b_t	0.22 (0.05)	0.00	0.38 (0.05)	0.00					
tax_t	−0.56 (0.30)	0.06	−0.44 (0.26)	0.08										
MLL=468.33					MLL=432.17					MLL=566.65				
S.C.=-4.25					S.C=-3.92					S.C.=-5.29				

Standard errors in parentheses.

MLL is the maximum log likelihood; S. C. is the Schwarz information criterion.

Regions included: AND, AST, CAN, CANT, CLM, CYL. EXT, GAL, MUR, VAL

Table A2: Low unemployment group of regions. OLS and GMM estimation.

Labour demand: n_{it}					Wage setting: w_{it}					Labour supply: l_{it}				
	OLS		GMM			OLS		GMM			OLS		GMM	
	coef.	p-value	coef.	p-value		coef.	p-value	coef.	p-value		coef.	p-value	coef.	p-value
$n_{i,t-1}$	1.15 (0.07)	0.00	1.06 (0.07)	0.00	$w_{i,t-1}$	0.50 (0.05)	0.00	0.47 (0.06)	0.00	$l_{i,t-1}$	0.68 (0.06)	0.00	0.63 (0.06)	0.00
$n_{i,t-2}$	−0.47 (0.07)	0.00	−0.41 (0.07)	0.00	u_{it}	0.27 (0.09)	0.00	0.33 (0.09)	0.00	w_{it}	−0.10 (0.04)	0.00	−0.09 (0.04)	0.02
$w_{i,t}$	−0.13 (0.04)	0.00	−0.17 (0.04)	0.00	$u_{i,t-1}$	−0.33 (0.10)	0.00	−0.40 (0.10)	0.00	w_{it-1}	0.09 (0.04)	0.00	0.09 (0.03)	0.01
$k_{i,t}$	0.90 (0.20)	0.00	1.10 (0.20)	0.00	pr_{it}	0.29 (0.06)	0.00	0.22 (0.06)	0.00	pop_{it}	0.99 (0.26)	0.00	1.11 (0.25)	0.00
$k_{i,t-1}$	−0.67 (0.20)	0.00	−0.84 (0.19)	0.00	b_t	0.27 (0.07)	0.00	0.31 (0.07)	0.00	pop_{it-1}	−0.51 (0.28)	0.00	−0.56 (0.22)	0.04
oil_t	−0.02 (0.007)	0.03	−0.02 (0.006)	0.01										
tax_t	−1.22 (0.29)	0.00	−1.21 (0.28)	0.00										
MLL=333.74					MLL=320.87					MLL=395.71				
S.C.=-4.54					S.C.=-4.16					S.C.=-5.22				

Standard errors in parentheses.

MLL is the maximum log likelihood; S. C. is the Schwarz information criterion.

Regions included: ARA, BAL, CAT, MAD, NAV, PV, RIO