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ABSTRACT

Spanish Regional Unemployment Revisited: The Role of Capital Accumulation*

This paper provides new evidence for the evolution of regional unemployment rates in Spain over the 1980-2000 period. We argue that interactive dynamic systems of labour demand, wage setting, and labour force equations (i) allow for a richer interpretation of regional disparities, and (ii) can capture the unemployment effects of growing variables such as capital stock. After classifying the 17 Spanish regions into high and low unemployment groups using kernel and cluster techniques, we estimate a structural labour market model for each group and evaluate the unemployment contributions of investment, benefits, taxes, and the oil price. We find that the main driving force of regional unemployment swings is capital accumulation.

JEL Classification: R23, J64

Keywords: regional unemployment, disparities, capital accummulation, kernel, cluster

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1 Introduction

European economies witnessed a substantial reduction in their aggregate unemployment rates during the early years of the naughties, especially those ones with a serious problem in the previous decades. If the 1990s were characterised by prolonged and persistent unemployment rates, the rapid reduction in the early 2000s brought a different set of issues to surface, like, for instance, the increase in the degree of discrimination of certain labour market participants (e.g. females, young workers), the effect of older workers in the public pension schemes, and the aggregate impact of massive immigration into Europe. Furthermore, the current recession underlines the fragility of such a "fast-drop" process as unemployment soared within a period of few months, especially in Spain, a country that tops the European ranking in employment destruction rates.

Among the new concerns, the increase in the degree of regional unemployment disparities has been the focus of an increasing body of literature (see inter alia Blanchard and Katz, 1992, Taylor and Bradley, 1997, Jimeno and Bentolila, 1998, or Bande et al., 2008). While the existence of disparities in the regional unemployment rates has important repercussions, from an economic policy and welfare perspective, the dominant paradigm in the literature has not dealt with this issue.[1] Actually, regional disparities in unemployment rate are a challenge to the standard labour market theories, since the neoclassical model can explain neither their existence nor their persistence.

If labour markets are flexible and product markets competitive, a negative shock that increases regional unemployment should be followed by two types of complementary responses. First, unemployed workers would accept lower real wages to find a new job - real wage flexibility is an assumed characteristic of the labour market. In addition, if a worker does not find a suitable job, s/he will migrate to other areas and, thus (controlling for regional amenities), labour compensation will be equalised across regions in the long run - labour mobility is another assumed characteristic of the labour market. The second response involves the behaviour of firms: when regional unemployment increases and real wages fall, new firms would move into the region (assuming free entry and exit of capital) to take advantage of the lower labour costs.

However, empirical evidence shows that disparities not only do not vanish in the medium/long run, but that they can be highly persistent, or, even worse, they can increase dramatically through time (see Limosani, 2004, for the Italian case, and Bande et al., 2008, for the Spanish case). Consequently, several authors have tried to explain regional disparities through various approaches and theories. Elhorst (2003) provides an informative summary and intelligible discussion of the debate. His main conclusion is 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 force participation decisions.

The contribution of this paper is to examine the regional unemployment problem through a dynamic multi-equation model that features spillover effects. Our framework of analysis is

[1] See Elhorst (2003) for a thorough and brief account of the topic.

based on the chain reaction theory (CRT), which views the evolution of unemployment as the interplay of dynamics and shocks within a system of labour demand, wage setting, and labour force equations.[2] In a nutshell, the salient characteristics of the CRT methodology are discussed below.

The dynamics of the system arise from a variety of sources, well known in the literature, and capture (i) employment adjustments due to hiring and firing costs, (ii) real wage adjustments due to nominal wage and price staggering, and (iii) labour supply adjustments due to the financial and phychological costs of entering and exiting the labour force. "Shocks" in the CRT methodology, in contrast to traditional simultaneous equations (SE) and vector autoregressions (VARs), are defined as changes in the exogenous variables. Since different regions may be exposed to different types of shocks and experience different adjustment processes, the chain reaction approach opens a new avenue for explaining regional unemployment disparities.

Defining the impulse (shock) as a change in an exogenous variable, rather than as a one-off change in the residuals of a behavioural equation has two advantages.[3] First, it allows the evaluation of 'contributions', a measure that shows how the endogenous variable of a dynamic equation is influenced by the actual changes in an exogenous variable over a sample interval (see Section 5). Second, unlike SE and VARs, identification of policy effects is not a problem in CRT models, since changes in the exogenous variables depend on policy changes. Clearly, spillovers are created when endogenous variables have explanatory power in other equations of the system. The reason that the inherent 'simultaneity' element of CRT models is labeled as 'spillovers' is to emphasise the plethora of interactive mechanisms contained in the system of equations, and highlight their importance in evaluating the dynamic 'contributions' of shocks to regional unemployment developments. So speaking, the 'chain reaction' epithet flags the crucial role that intertemporal responses have in the evolution of the unemployment rate. Finally, we should point out that CRT modelling builds on the bidirectional feedback between theory (or a prior viewpoint) and evidence; this is in sharp contrast to SE and (structural) VARs that aim at bridging the (perceived so) compartmentalised areas of theoretical analysis and applied work.[4]

We apply the CRT methodology to the Spanish case, one of the European economies characterized by large, persistent and increasing disparities in its regional unemployment rates. In particular, we extend the work of Bande and Karanassou (2009) by using a revised data set that spans a longer period of time, and provide evidence that reinforces their results and further clarifies the topic under investigation. An implication of our work is that policy makers should be aware that each group of regions responds differently to labour market changes associated with the various policy stimuli. For example, fiscal policy directed towards the reduction of unemployment should take into account that it might generate quite different outcomes if regional

[2] 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.

[3] As Blanchard (2009, p. 220) correctly points out, "The use of "shocks" is fraught with philosophical, but also with practical, difficulties: Technological shocks, animal spirits, changes in perceived uncertainty, etc. all have deeper causes, which themselves have even deeper causes, and so on."

[4] See Karanassou and Sala (2009b) for a detailed analysis of the various methodological issues concerning CRT models, SE, and (structural) VARs.

employment elasticities with respect to investment are idiosyncratic.

One important finding of this study is that the main driving force of regional unemployment swings is capital accumulation. This result challenges the dominant paradigm, namely that trended variables (such as capital stock) cannot influence unemployment (Layard et al., 1991, LNJ heafter; reprinted in 2005), and gives credit to the fast growing literature about the significant role of capital accumation in shaping unemployment movements.

Contrary to the thesis of Layard et al. (1991, p.107) that "If the production function is Cobb-Douglas (not a bad assumption) and benefit replacement rates are kept stable, then unemployment in the long run is independent of capital accumulation and technical progress", Rowthorn (1999) argues that if the elasticity of substitution between capital and employment is less than unity, which typically is the case, the capital-employment ratio affects unemployment; Karanassou and Snower (2004) argue that capital stock can determine long-run unemployment, since equilibrating mechanisms in the labour market and other markets jointly guarantee its trendless property; Kapadia (2005) augments the standard Cobb-Douglas production function by introducing capacity constraints and endogenising investment, and shows that capital stock affects the equilibrium unemployment rate.

There is ample evidence by various authors using different methodologies that capital accumulation is a major driving factor in the unemployment trajectory. For instance, Arestis and Biefang-Frisancho Mariscal (1998, 2000) using a wage determination model find that high and persistent unemployment rates in the UK and Germany were, to a significant extent, caused by capital shortages. In addition, Malley and Moutos (2001) use a variant of the LNJ framework and show that, for 20 OECD countries, the unemployment rate is affected in the long-run when domestic and foreign capital stocks grow at unequal rates. Furthermore, Arestis et al. (2007) document a negative capital-unemployment relationship in nine EMU countries, and Karanassou et al. (2008, 2009a, 2010) show that capital accumulation plays a fundamental role in shaping unemployment movements in the Nordic countries, Spain, and Australia, respectively. Also, Blanchard (2000), Sawyer (2002), Herbertson and Zoega (2002), Smith and Zoega (2005), are some examples of papers that find a negative relationship between aggregate investment levels and the unemployment rate. Finally, in a regional level context, Bande and Karanassou (2009) show that capital stock growth is the major determinant of unemployment in the Spanish regions, and Kunz (2009) finds that the level of investment has the strongest influence on German regional unemployment.

The rest of the paper is organized as follows. Section 2 examines regional unemployment disparities in Spain using kernel density functions and cluster analysis. Section 3 puts our theoretical analysis against the conventional one, and sketches the structure of the regional model. Section 4 discusses our estimation methodology and empirical results. Section 5 evaluates the contributions of the exogenous variables to the evolution of regional unemployment during the three major swings of the eighties and nineties. Finally, Section 6 concludes and gives suggestions for future work.

2 The Distribution of Regional Unemployment in Spain

The Spanish unemployment rate has been among the highest of the European Union during the last decades and has received much attention in the literature. In addition to the high unemployment rate levels (and high unemployment persistence) an important regional dimension should be noted: the dramatic increase in the degree of regional unemployment disparities.

The evolution of regional disparities in the unemployment rate may be viewed under different perspectives. According to Marston (1985), the existence of regional unemployment disparities may reflect either (i) an equilibrium outcome - disparities exist in the long-run equilibrium of the economy because regions show different natural rates of unemployment (determined by demand, supply and institutional variables which evolve steadily through time), or (ii) a disequilibrium outcome - disparities exist because regional labour markets adjust differently to common shocks, giving rise to a polarisation effect.

Blanchard and Katz (1992), BK, show that the US regional unemployment disparities are not persistent due to 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 (as the large fraction of unemployed workers puts downward pressure on flexible wages). Although the influential BK model, focusing exclusively on idiosyncratic shocks in a perfect labour mobility framework, had a strong impact on the regional labour market literature (see inter alia, Decressin and Fatas, 1995, Jimeno and Bentolila, 1998, Fredriksson, 1999, and Elhorst, 2003), it is not exempt from problems. Bartik (1993), and Rowthorn and Glyn (2006) show that the BK results are seriously affected by the small sample bias inherent in short time series data, and the large measurement errors in survey based series of the employment status at state level. Correcting for these biases, they find no support for the assumption of a highly flexible regional labour market in the US.

Bande et al. (2008, 2010b) show that the evolution of regional disparities in Spain is associated with significant imitation effects in wage bargaining. They find that usually the less productive sectors in the less productive regions link their wage growth to that prevailing in the most productive sectors of the most productive regions. As a result, the increase in unit labour costs limits the ability to create employment during economic upturns. Bande and Karanassou (2009) examine the labour markets of two groups of Spanish regions, and find that their idiosyncratic unemployment adjustments to region-specific and national shocks lead to an increase in unemployment rate disparities.

2.1 Changes in the Regional Unemployment Distribution

Let us look at the recent evolution of regional unemployment disparities in Spain through a simple analytical tool, the estimation of kernel density functions for the relative regional unemployment rates (i.e., the regional unemployment rate over the aggregate one). We estimate the density of regional relative unemployment rates using a kernel density estimator along the lines suggested by Quah (1997), Overman and Puga (2003), or López-Bazo et al. (2005).

A kernel function is given by

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

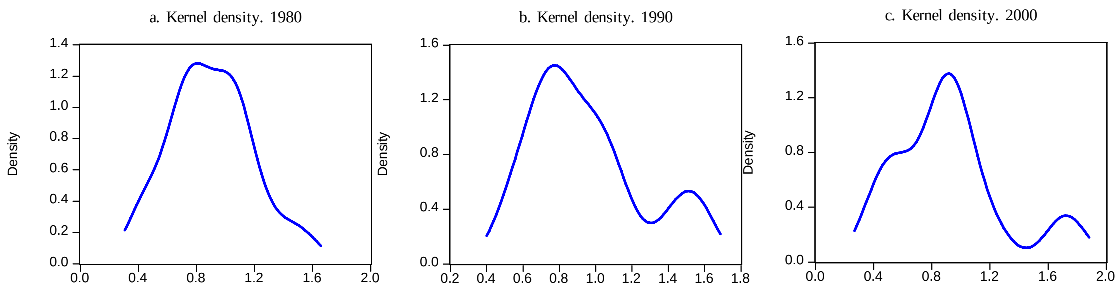
and a class of density estimators (the Ronsenblatt-Parzen kernel density estimators) can be defined as:

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

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

Using regional unemployment data from the Spanish Labour Force Survey (EPA) from 1980 to 2000,[6] we estimate the kernel density at the start of each decade and analyse its shape (see Figure 1).

Figure 1. Kernel density functions. Relative unemployment rates



The first panel in Figure 1 plots the estimated distribution in 1980. Note that, although regional unemployment rates are virtually normally distributed around the national unemployment rate (i.e., the mean/mode of relative unemployment rates is unity), an incipient two-mode distribution is evident. In fact, by 1990, the picture becomes completely different. The kernel distribution has a clear bimodal shape (Figure 1b), one centered around 0.8 and another one centered around 1.5. This result suggests that the eighties were characterised by a divergence process in the Spanish regional unemployment rates. A number of regions reduced their unemployment rates with respect to the national average, while a number of regions evolved in the opposite direction (with higher relative unemployment rates). Finally, according to the third panel in Figure 1, this divergence intensified during the nineties. The plot of the kernel density for the year 2000 shows that, while the group of regions with low relative unemployment rates stabilised around 0.8, the high relative unemployment group shifted to the right (i.e., to a larger

[5] The findings below are not affected by the use of alternative kernel functions. Results are available upon request.

[6] In 2001 the Spanish Statistical Institute (INE) introduced major changes in the questionarie of its survey - application of the new methodology post 2001 led to the time series heterogeneity of regional unemployment rates. Thus, we are restricted to use the homogeneous 1980-2000 sample.

relative unemployment rate around 1.8).[7]

Thus, the above kernel analysis suggests that the evolution of regional unemployment rates in Spain over the 1980-2000 period led to the formation of two groups of regions: one with low relative unemployment rates, and another one with high relative unemployment rates.

2.2 Who is who? Cluster Analysis of Spanish Regional Unemployment

In order to identify which regions should be included in each group, a clustering analysis is conducted (see Everitt et al., 2001, for various examples on cluster analysis). On the basis of the kernel density analysis results, exogenous regional data are used to identify the two groups of regions, namely, a first group that has increased its relative unemployment rate throughout the sample, and a second one that has improved its relative position. The classification criteria have been designed according to regional data on the participation rate, the relative per capita income level, and the relative unemployment rate. Our aim is not to group regions according to the performance of their unemployment rate alone, as this would yield an endogenous classification, but rather to group them as a function of the socioeconomic elements that influence such unemployment performance. There are several potential candidate exogenous variables that could be considered, but among the most important, and following Bande et al. (2008), we consider the participation rate and the per capita income level as proxies of social welfare.

Participation rates differ a lot across regions and depend on the socioeconomic and political environment. In the less developed regions, participation rates are higher because labour returns (productivity) are very low. On the contrary, in the most developed areas, the efficiency of labour and high productivity allow, theoretically, for a lower participation rate. This argument, nevertheless, is purely theoretical and does not take into account the role of the welfare state: in developed regions, participation rates could be lower due to more generous social protection schemes. Regional authorities may provide better public goods and social benefits, given their higher tax revenues, and thus participation could be reduced. In the less developed regions, however, regional authorities cannot guarantee the same level of protection, and thus participation could be higher.

The per capita income level,on the other hand, is the main indicator of the economic performance and one of the key variables related to regional convergence issues. Rich and poor regions are often classified depending on the value of this indicator. The results of the cluster analysis are summarised in Table 1.

According to Table 1, the two groups consist of the following regions. The 'high unemployment' group is formed by Andalucía, Asturias, Canarias, Cantabria, Castilla-León, Castilla-La Mancha, Extremadura, Galicia, Murcia and Comunidad Valencia, while the 'low unemployment' group is formed by Aragón, Baleares, Cataluña, Madrid, Navarra, País Vasco and La Rioja. This classification is almost identical to that of Bande and Karanassou (2009), despite using the shorter sample period 1980-1995 and the relative unemployment as the sole classifica-

[7] Note that a third group might be identified, comprising the regions with unemployment rates around half the size of the Spanish average (Bande et al., 2008). Also, at the provincial level, Lopez-Bazo et al. (2005) find two peaks in the distribution with strong persistence through time.

tion criterion; the only difference in the current classification is the inclusion of Pais Vasco in the low unemployment group, instead of the high unemployment one.[8] Naturally, the first group is characterised by larger relative unemployment rates, lower relative per capita income levels, and higher participation rates, whereas the second group is characterised by lower unemployment, higher per capita income levels and lower participation rates.

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.
Rel. p.c. is relative per capita.

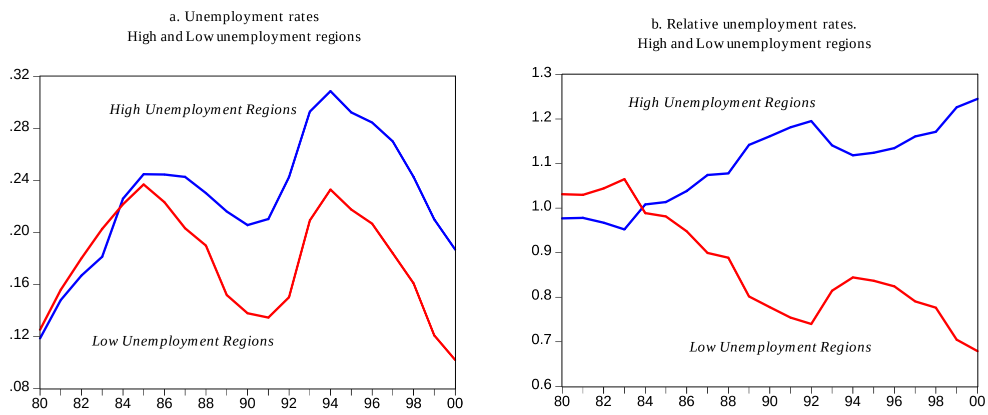
Figure 2 plots the absolute and relative unemployment rates within each group. The evolution of relative unemployment rates (Figure 2b) unveils a dramatic increase in the disparities between the high and low unemployment regions. The group of high unemployment regions has experienced a persistent increase in its relative unemployment rate since 1983, the only exception being the 1992-1994 period when the relative unemployment rate briefly decreased. At the same time, the low unemployment rate group has witnessed a sustained reduction in its relative unemployment rate, except again during the recession period in the early nineties. Note also that, during the recession in the beginning of the eighties, the high unemployment group was in fact a 'low unemployment' group, having its classification status modified in 1984.

Furthermore, Figure 2b portrays the counter-cyclical behaviour of regional unemployment disparities: during the booming years of 1985-1991 and 1994-2000 the distance between the relative unemployment rates of the high and low groups increases markedly, whereas during the 1992/93 recession the disparities are reduced. This behaviour is characteristic of the Spanish regional labour market. Bande et al. (2008) find that the concurrence of the 1985-1991 booming period with the decentralisation of wage bargaining (from a previously highly centralised and coordinated system) gave rise to an important imitation effect. This effect allowed less productive

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

firms in the less productive regions to link their wage growth to the performance of the most productive firms in the most productive regions, thus increasing unit labour costs and slowing down employment creation.

Figure 2. Unemployment rates and relative unemployment rates



Bande and Karanassou (2009) argue that this evolution of disparities can be explained by a combination of (i) different unemployment responses to similar shocks (due to different adjustment dynamics) and (ii) different degrees of labour market flexibility, such that some regions adjust faster than others when facing the same labour market shock. They find that during good times high unemployment regions do not benefit as much (in terms of their unemployment reduction) as low unemployment regions, whereas the exact opposite holds during bad times. This explains why regional disparities in Spain show a profound counter-cyclical pattern.

Having identified the above two groups of clearly distinct economic features, we estimate stand-alone regional labour market models for each group of regions. Our empirical work in Section 4 stems from the chain reaction theory of unemployment and, whilst determining the driving forces of unemployment, it finds that there exist substantial regional disparities. Before we proceed with the empirical evidence, we analyse below the rationale of labour market behaviour through a stylised model of frictions and growth, and present the structure of our regional models.

3 Chain Reaction Theory (CRT)

The chain reaction theory views the evolution of the unemployment rate as the interplay of lagged adjustment processes and shocks in the labour market system. 'Lagged adjustment processes' refer to the dynamic nature of the labour market model which reflects hiring/firing costs, wage/price staggering, labour force entry/exit costs, etc., and 'shocks' represent changes in the exogenous variables of the system of equations. The interplay of lags and shocks across equations is facilitated by spillover effects, which arise when endogenous variables have explanatory power in other equations of the system (for example, wages in the labour demand and labour force equations, or the unemployment rate in the wage setting equation). Thus, the 'chain reaction' epithet stands for the intertemporal responses of the unemployment rate to changes in the exogenous variables (shocks).

Before we discuss the analytical details of the CRT framework, it is worthwhile to outline the conventional natural rate of unemployment (NRU) approach.

3.1 Natural Rate of Unemployment (NRU)

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. Let us summarize the salient characteristics of this approach by using a rather simplistic version of this type of models.

First, assume that real wages are set by wage bargaining, such that the wage equation may be written as

$$W_t - P_t^e = \alpha_0 - \alpha_1 u_t + \alpha_2 x_t + \varepsilon_t^w, \tag{1}$$

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 vector of exogenous variables in logarithms that affect wage setting (wage-push variables, such as minimum wages, unemployment benefits, etc.), ε_t^w is a random shock to wage setting, and the α's are positive constants.

Prices are set by firms operating in non-competitive markets as a markup over their labour unit costs. Thus, the price equation may be written as

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

where μ_0 is a function of the price-elasticity of product demand, and ε_t^p is a random shock to price setting.

Expressing both equations (1) and (2) in terms of the nominal wage and setting them equal to each other gives:

$$\alpha_0 + P_t^e - \alpha_1 u_t + \alpha_2 x_t + \varepsilon_t^w = P_t - \mu_0 - \varepsilon_t^p;$$

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

$$u_t = \frac{\alpha_0 + \mu_0}{\alpha_1} + \frac{(P_t^e - P_t)}{\alpha_1} + \frac{\alpha_2}{\alpha_1} x_t + \frac{\varepsilon_t^w + \varepsilon_t^p}{\alpha_1}. \tag{3}$$

Some key implications of the reduced form unemployment rate equation (3) should be noted. First, as Friedman argued in his influential 1968 paper, in the long run, since expectations must be correct and shocks cancel out, unemployment must be at its natural level, u_t^n:

$$u_t^n = \frac{\alpha_0 + \mu_0 + \alpha_2 x_t}{\alpha_1}. \tag{4}$$

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 and temporary shocks. The speed of adjustment to transient random errors depends on wage flexibility, namely the response of wages to labour market conditions as reflected in parameter α_1.

Second, equation (4) shows that the natural rate of unemployment (NRU) depends on markups, labour market institutions, and wage flexibility. 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 NRU models, growing variables - such as labour productivity, capital stock, and working age population - play no role in determining the long-run unemployment rate.

Despite the popularity of the NRU approach, various strands of the macro-labour literature have established that an important dimension of the unemployment problem is that employment, wage setting, and labour force participation decisions are characterised by significant lags. Furthermore, the CRT argues that these lags interact with one another, and, thus, supports the use of dynamic multi-equation systems to model the structure of the labour market and explain the evolution of the unemployment rate.

As a result of the interplay of lagged adjustment processes and growing variables, the predictions of the CRT lie in stark contrast to the unemployment rate predictions of the single-equation dynamic models of the NRU and structuralist theories.[9] As we show below, CRT models can accommodate the interplay of dynamics and growth via the univariate representation of unemployment, which is derived from an estimated labour market system, instead of estimating the single-equation of a reduced form unemployment rate model. This key difference between the two approaches 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. 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).

3.2 A Stylised CRT Model

In the context of autoregressive multi-equation models, movements in unemployment can be viewed as 'chain reactions', intertemporal responses, to labour market shocks. The network of interacting lagged adjustment processes, which are well documented in the literature,[10] is the propagation mechanism for these chain reactions. 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

[9] Like the NRU equation (3), the structuralist equations are dynamic reduced form single-equation models. Phelps (1994) offers a comprehensive account of the structuralist theory. See also Karanassou, Sala, and Snower (2010) for a compare and contrast discussion of the chain reaction and structuralist theories.

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

and exiting from the labour force.[11] By identifying the various lagged adjustment processes, the CRT can explore their interactions and evaluate the unemployment contributions of the interplay between the labour market dynamics and the shocks to the system.

To illustrate the workings of the CRT we use an analytical model that is in line with the estimated labour market model in Section 4. Consider the following stylised system of labour demand, real wage, and labour supply equations:[12]

$$
\begin{aligned}
n_t &= \alpha_1 n_{t-1} + \beta_1 k_t - \gamma_1 w_t \quad \text{or} \quad (1-\alpha_1 L)\, n_t = \beta_1 k_t - \gamma_1 w_t, & (5)\\
w_t &= \alpha_2 w_{t-1} + \beta_2 x_t - \gamma_2 u_t \quad \text{or} \quad (1-\alpha_2 L)\, w_t = \beta_2 x_t - \gamma_2 u_t, & (6)\\
l_t &= \beta_3 z_t + \gamma_3 w_t, & (7)
\end{aligned}
$$

where n_t is employment, w_t is real wage, and l_t is labour force, k_t is the capital stock, x_t is labour productivity z_t is the working age population, the autoregressive parameters are $|\alpha_1, \alpha_2| < 1$, the β's and γ's are positive constants, and L is the lag operator. All variables are in logs. The unemployment rate (not in logs) is

$$u_t = l_t - n_t, \tag{8}$$

which, as Gali (2010) points out, for rates of unemployment of the magnitude observed in the postwar economies, is a close (and algebraically convenient) approximation to the more conventional measure of the difference between the levels of labour force and employment as a percent of labour force, $(L_t - N_t)/L_t$.

Note that the γ's generate spillover effects, since they allow changes in an endogenous variable to affect the other equations in the system. Put differently, changes in an exogenous variable in one equation, say capital stock in labour demand, also affect the real wage equation (via γ_2) and then the labour supply equation (via γ_3). Similarly, although labour productivity appears as a determinant of wages, it also affects labour demand (via γ_1) and labour supply (via γ_3). We further clarify the spillover effects with the univariate representation of unemployment analysed below.

Multiplying both sides of labour demand (5) and supply (7) equations by the lag polynomials $(1-\alpha_2 L)$ and $(1-\alpha_1 L)(1-\alpha_2 L)$, respectively, and then substituting into it the real wage equation (6), gives

$$(1-\alpha_1 L)(1-\alpha_2 L)\, n_t = (1-\alpha_2 L)\beta_1 k_t - \gamma_1 \beta_2 x_t + \gamma_1 \gamma_2 u_t, \tag{9}$$

$$(1-\alpha_1 L)(1-\alpha_2 L) l_t = (1-\alpha_1 L)(1-\alpha_2 L)\beta_3 z_t + (1-\alpha_1 L)\gamma_3 \beta_2 x_t - (1-\alpha_1 L)\gamma_2 \gamma_3 u_t. \tag{10}$$

Next, we derive the univariate representation (or reduced form dynamics) of the unemployment

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

[12] For ease of exposition, and without loss of generality, this illustration ignores constants and error terms. However, the augmented version of the labour market model estimated in Section 4 includes constants, other explanatory variables, and the second lags of the dependent variables. Furthermore, it can be shown that the above labour market model is compatible with standard microeconomic foundations.

rate by inserting equations (9) and (10) into definition (8):[13]

$$\begin{aligned}\left[(1-\alpha_1 L)(1-\alpha_2 L)+(1-\alpha_1 L)\gamma_2\gamma_3+\gamma_1\gamma_2\right]u_t &= -(1-\alpha_2 L)\beta_1 k_t \\ &\quad +\left[\gamma_1\beta_2+(1-\alpha_1 L)\gamma_3\beta_2\right]x_t \\ &\quad +(1-\alpha_1 L)(1-\alpha_2 L)\beta_3 z_t.\end{aligned} \tag{11}$$

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.

According to the derived equation (11), if unemployment does not put downward pressure on wages, $\gamma_2 = 0$, changes in the capital stock (k_t) and working age population (z_t) do not spillover in the labour market and, thus, the overall effect of these variables on unemployment can be measured, respectively, by the labour demand (5) and labour force (7) equations. Also, observe that if the wage elasticities are zero, $\gamma_1 = \gamma_3 = 0$, labour productivity (x_t) does not influence unemployment.

Algebraic manipulation of equation (11) leads to the following unemployment rate dynamics:

$$u_t = \phi_1 u_{t-1} - \phi_2 u_{t-2} - \theta_0^k k_t + \theta_1^k k_{t-1} + \theta_0^x x_t - \theta_1^x x_{t-1} + \theta_0^z z_t - \theta_1^z z_{t-1} + \theta_2^z z_{t-2}, \tag{12}$$

where $\phi_1 = \frac{\alpha_1+\alpha_2+\alpha_1\gamma_2\gamma_3}{1+\gamma_1\gamma_2+\gamma_2\gamma_3}$, $\phi_2 = \frac{\alpha_1\alpha_2}{1+\gamma_1\gamma_2+\gamma_2\gamma_3}$, $\theta_0^k = \frac{\beta_1}{1+\gamma_1\gamma_2+\gamma_2\gamma_3}$, $\theta_1^k = \alpha_2\theta_0^k$, $\theta_0^x = \frac{(\gamma_1+\gamma_3)\beta_2}{1+\gamma_1\gamma_2+\gamma_2\gamma_3}$, $\theta_1^x = \alpha_1\beta_2\gamma_3\theta_0^x$, $\theta_0^z = \frac{\beta_3}{1+\gamma_1\gamma_2+\gamma_2\gamma_3}$, $\theta_1^z = (\alpha_1+\alpha_2)\,\theta_0^z$, and $\theta_2^z = \alpha_1\alpha_2\theta_0^z$.

The univariate representation (12) highlights several features of the CRT modelling. First, the autoregresive parameters ϕ_1 and ϕ_2 embody the interactions of the employment and wage setting adjustment processes (α_1 and α_2, respectively). Second, the contemporaneous coefficients of the exogenous variables (the θ_0's) embody the feedback mechanisms built in the system, since they are a function of the short-run sensitivities of the individual equations (the β's) and the spillover effects (the γ's). Third, the interplay of the dynamics across equations is emphasized by the lagged structure of the exogenous variables; using time series jargon, we refer to the lagged exogenous variables as "moving-average" terms.

Another key element of the chain reaction approach is that trended variables (such as capital stock and working age population) drive unemployment, which, as noted in the previous section, contradicts the dominant NRU view. Let us explain how trended variables can influence the time path of the stationary unemployment rate. Capital stock and working age population initially enter the system as determinants of the trended employment and labour force variables, respectively. Labour demand (5) is a balanced equation due to dynamic stability, $|\alpha_1| < 1$, while the static labour supply (7) is balanced by default. The labour demand (9) and supply (10) equations remain balanced once the wage has been substituted into them. Consequently, the univariate representation of unemployment (12) is a balanced equation, since it is given by the difference of the dynamically stable labour supply and labour demand equations.

Since different regions may be exposed to different types of shocks and experience differ-

[13] The term 'reduced form' means that the parameters of the equation are not estimated directly - they are simply some nonlinear function of the parameters of the underlying labour market system.

ent lagged adjustment processes, the CRT approach has a clear advantage over the standard single-equation NRU models in explaining regional unemployment disparities. In the next section we use a regionally adapted version of the above CRT model to examine the evolution of regional unemployment in Spain during the period 1980-2000. In what follows we first discuss the characteristics of such a model.

3.3 Structure of the Regional Model

We use a structural vector autoregressive distributed lag model for the Spanish regions to analyse regional unemployment persistence and explain unemployment rate disparities:[14]

$$\mathbf{A}_0\mathbf{y}_{it} = \mathbf{A}_1\mathbf{y}_{i,t-1} + \mathbf{A}_2\mathbf{y}_{i,t-2} + \mathbf{B}_0\mathbf{x}_{it} + \mathbf{B}_1\mathbf{x}_{i,t-1} + \mathbf{C}_0\mathbf{z}_t + \mathbf{C}_1\mathbf{z}_{t-1} + \mathbf{e}_{it}, \tag{13}$$

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 identically independently distributed error terms.

The multi-equation system (13) consists of a

- labour demand equation, describing equilibrium employment (n_{it}),
- wage setting equation, describing real wage (w_{it}) determination, and
- 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 system (13) the regional unemployment rate is determined by 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) emphasize regional dynamics, as opposed to national dynamics, and analyse exclusively the effects of region specific shocks.

Each group of regions is modeled along the lines of the structural system (13). Our model does not take into account any labour or firm mobility between the high and low unemployment groups of regions. The absence of labour mobility between the two groups of regions can be justified on the basis of insufficient regional wage differentials, important regional differences in housing prices, and increasing family support for the young who are the bulk of emigrants (see inter alia de la Fuente, 1999, Attanasio and Padoa-Schioppa, 1991, Antolin and Bover, 1997, and Bentolila, 1997, for arguments in support of this view). Furthermore, official statistics on internal migrations show a very limited impact of population movements. Jimeno and Bentolila (1998) find that labour mobility does not play a significant role in explaining regional labour market adjustments - this is achieved through labour force participation rather than migration.

[14] The dynamic system (13) 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 all of the estimated equations in Section 4 below satisfy this condition.

Regarding firm mobility, the reason that firms do not move from low to high unemployment regions, where wages could be lower,[15] is that high unemployment regions in Spain are generally peripheral and have an inadequate endowment of public infrastructures (highways connecting poor regions with richer ones were finished during the last decade, for instance).[16] This leads to higher transportation costs and thus limits the willingness of firms to move. Also, Spanish firms would not move to lower wage regions due to agglomeration effects.[17] When firms locate close to large markets, they enjoy positive agglomeration externalities and increasing returns to scale. Hence, moving to another region would imply an overall increase in costs (the lower wage does not compensate for the loss of these externalities). In fact, firms have tended to locate mainly in the richer regions of Madrid, Ebro Axis and the Mediterranean coast.

The following sections aim at identifying the causes of regional unemployment in Spain by examining the interplay of labour market lags and region-specific/national shocks in the high and low unemployment groups of regions.

4 Empirical Methodology

Our empirical regional model is an augmented version of the CRT system analysed in the above section. Thus, our estimated system comprises labour demand, wage setting and labour force equations, and covers two panels of regions. A panel for the group of the ten high unemployment rate regions and a panel for the group of the seven low unemployment rate regions, according to the results of the kernel and cluster analysis in Section 2.

4.1 Data Description

For a robust analysis of the evolution of regional unemployment disparities an extensive set of observations is needed - panel data estimation allows us to use 210 and 147 observations for the high and low unemployment rate panels, respectively. The advantages of pooling the observations on a cross section of regions over several time periods are numerous and well documented in the literature.[18]

The data sources are (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*). The sample frequency is annual and the period of analysis is 1980-2000, due to data limitations.[19] Table 2 gives the definitions of the variables.

[15] Maza and Villaverde (2009) find that, since the mid eighties, a process of wage convergence has taken place, thus reducing the advantages of firms moving from one region to another.

[16] Despite the high effort by the EU to improve the infrastructure endowments of poor regions, European regional funds have not succeeded in improving the performance of the high unemployment regions relative to the rest of the country. See Bande et al. (2010a) for a discussion.

[17] See Krugman (1998) for the arguments of the new economic geography on agglomeration effects.

[18] See, for example, Hsiao (1986) and Baltagi (1995) for a detailed exposition of stationary panel data estimation.

[19] The reason for restricting our analysis to the 1980-2000 period is twofold. First, the regional capital stock series are obtained from the BD-MORES dataset which currently covers the 1980-2005 period (see Dabán *et al.*,2002, for a detailed description). Second, in 2001 the Spanish Statistics Institute *(INE)* introduced fundamental changes in the Labour Force Survey (mainly related to the definition of labour force) in order to make the survey comparable

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 indirect tax rate, tax_t.

4.2 The Econometric Model

We estimate the lagged adjustment processes and sensitivities of the system of behavioural equations (13) by using a fixed-effects (FE) type of model:

$$\begin{aligned}\mathbf{A}_0\mathbf{y}_{it} &= \mathbf{A}_1\mathbf{y}_{i,t-1} + \mathbf{A}_2\mathbf{y}_{i,t-2} + \mathbf{B}_0\mathbf{x}_{it} + \mathbf{B}_1\mathbf{x}_{i,t-1} + \mathbf{C}_0\mathbf{z}_t + \mathbf{C}_1\mathbf{z}_{t-1} + \mathbf{e}_{it}, \\ \mathbf{e}_{it} &= \boldsymbol{\mu}_i + \mathbf{v}_{it},\ i = 1, ..., N,\ t = 1, ..., T. \end{aligned} \tag{14}$$

Equation (14) shows that the vector of disturbances ($\mathbf{e}_{it}$) follows a one-way error component model,[20] 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.

The FE estimator is the most common estimator of dynamic panels,[21] and in homogenous dynamic panels (i.e. models with constant slopes) the FE estimator is consistent as $T \to \infty$, for fixed N.[22] Baltagi and Griffin (1997) compare the performance of a large number of homogenous and heterogeneous estimators and provide evidence in support of the FE estimator. In particular, they find that (i) individual unit estimates (both OLS and 2SLS) exhibit substantial variability, whereas pooled estimators provide more plausible estimates, and (ii) accounting for potential endogeneity is "disappointing as the 2SLS estimators performed worse than their counterparts assuming all variables are exogenous."

Dynamic panel data and nonstationary panel time series models have attracted a lot of attention over the past decade, and thus, 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.[23] Before using stationary panel data estimation

to the Eurostat standards. The induced structural break in the labour force and unemployment rate series implies that the figures for these series are not fully comparable to the ones prior to 2001.

[20] This is a 3×1 vector representing the error terms of the labour demand, wage setting, and labour supply equations in our system.

[21] The fixed-effects estimator is also known as the least squares dummy variables (LSDV) estimator, or the within-group or the analysis of covariance estimator.

[22] 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.

[23] Banerjee (1999) and Baltagi and Kao (2000), and Smith (2000) provide an overview of the above topics and

techniques, we apply a series of unit root tests. In particular, we test the order of integration of the national (regional) variables using the KPSS unit root test (panel unit roots). Table 3 shows that for all four national variables - real oil price, real social security benefits, direct tax rate, and trade deficit - the KPSS tests cannot reject the null hypothesis of (trend) stationarity.[24]

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

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

4.2.1 Panel Unit Roots

We examine the stationarity of the regional variables using panel unit root tests, as it is widely accepted that pooling cross section and time series data offers more powerful unit root tests.[25] . We apply the simple statistic proposed by Maddala and Wu (1999) - this is an exact nonparametric test based on Fisher (1932):

$$\lambda = -2\sum_{i=1}^{N} \ln p_i \sim \chi^2 (2N), \tag{15}$$

where p_i is the probability value of the ADF unit root test for the ith unit (region). Since it combines the significance of N different independent unit root statistics, the Fisher test has the following advantages: (i) the autoregressive parameter is not restricted to be homogeneous across regions under the alternative of stationarity, (ii) the lag length and the inclusion of a time trend in the individual ADF regressions are determined separately for each region, and (iii) the sample sizes of the individual ADF tests can differ according to data availability for each cross-section. In addition, 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.[26]

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survey the developments in this technical and rapidly growing literature.

[24] Kwiatkowski-Phillips-Schmidt-Shin (1992) proposed the following statistic to test the null hypothesis of stationarity:

$$\text{KPSS}(\kappa) = \frac{\sum_{t=1}^{T} S_t^2}{T^2 s^2(\kappa)},$$

where T is the sample size, $S_t = \sum_{i=1}^{t} \widehat{\varepsilon}_i$ is the partial sum of the residuals when the series is regressed on an intercept (and possibly on a time trend), and $s^2(\kappa)$ is a consistent non-parametric estimate of the disturbance variance. In particular, $s^2(\kappa)$ is constructed as in Phillips (1987) or Phillips and Perron (1988) by using a Bartlett window adjustment based on the first κ sample autocovariances as in Newey and West (1987). KPSS report critical values (c.v.) for the case of (i) a constant in the auxilliary regression: 1% c.v.=0.74, 2.5% c.v.=0.57, 5% c.v.=0.46, 10% c.v.=0.35, and (ii) both a constant and a trend: 1% c.v.=0.22, 2.5% c.v.=0.18, 5% c.v.=0.15, 10% c.v.=0.12.

[25] See, for example, Levin and Lin (LL) (1993), Im, Pesaran and Shin (2003), Harris and Tzavalis (1999), Maddala and Wu (1999). 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 (Phillips and Moon, 1999).

[26] The asymptotic panel unit root tests developed by Levin and Lin (LL) are based on pooled regressions. The main criticism against LL tests is that, under the alternative of stationarity, the autoregressive coefficient is the same across all units (i.e. $H_1 : \rho_1 = \rho_2 = ... = \rho_N = \rho < 0$). This restrictive assumption is relaxed in the asymptotic test proposed by Im, Pesaran and Shin (IPS). Like the Fisher test, and in contrast to the LL tests,

Table 4 reports the Fisher statistics for all the regional 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.

On the basis of Tables 3 and 4, we proceed with the application of stationary panel data estimation techniques.

4.3 Estimation Results

Tables 5 and 6 show the estimated models for the high and low unemployment groups of regions, respectively. Note that, while the fixed effects model of each group estimates identical slope coefficients across regions, any differences in the labour market behaviour across units are effectively captured by the estimated regional constants (results are available upon request). According to the Schwarz model selection criterion the fixed-effect model is preferred to the heterogeneous models of individual (regional) time series regressions.[27]

In the labour demand equation, employment depends negatively on the real wage and positively on the level and the growth rate of the capital stock. Oil prices and direct taxes (as % of GDP) have a negative impact on labour demand, while the lagged employment term reflects the employment adjustment process due to, e.g., hiring/firing and training costs. In the wage setting equation, the real wage depends negatively on unemployment, and positively on productivity and benefits. The lag of real wage reflects the wage adjustment process due to, e.g., wage and price staggering. In the labour supply equation, the size of the labour force depends positively on working age population and negatively on the real wage (which indicates that the income effect dominates). The lagged labour force reflects the labour force adjustment process due to,

the IPS test is based on the individual ADF regressions for each of the N cross-section units. While the Fisher test uses the probability values of the individual ADF tests, the IPS uses their test statistics. Compared to the Fisher test, the disadvantage of the IPS test is that it implicitly assumes the same T for all countries and the same lag length for all the individual ADF regressions.

[27] 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) which is computed as follows:

$$\begin{aligned} SIC_{pooled} &= MLL - 0.5k_{pooled}\log(NT), \\ SIC_{individual} &= \sum_{i=1}^{j} MLL_i - N\left[0.5k_i \log(T)\right],\ j = 10, 7 \end{aligned}$$

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.)

e.g., costs of entry to and exit from the labour market. Finally, note that in all three equations the explanatory variables are statistically significant at conventional levels in both groups of regions.

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 (0.03)	0.00	$w_{i,t-1}$	0.62 (0.04)	0.00	$l_{i,t-1}$	0.78 (0.04)	0.00
$w_{i,t}$	−0.30 (0.04)	0.00	u_{it}	−0.49 (0.08)	0.00	w_{it}	−0.05 (0.01)	0.00
$k_{i,t}$	0.30 (0.03)	0.00	$u_{i,t-1}$	−0.61 (0.09)	0.00	pop_{it}	0.34 (0.06)	0.00
$\Delta k_{i,t}$	1.14 (0.22)	0.00	pr_{it}	0.20 (0.04)	0.00	Δpop_{it}	0.54 (0.22)	0.01
oil_t	−0.01 (0.006)	0.04	b_t	0.22 (0.05)	0.00			
tax_t	−0.56 (0.30)	0.06						
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; Δ denotes the difference operator.

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 6: Low 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
$n_{i,t-1}$	0.65 (0.04)	0.00	$w_{i,t-1}$	0.50 (0.05)	0.00	$l_{i,t-1}$	0.68 (0.06)	0.00
$\Delta n_{i,t-1}$	0.35 (0.04)	0.00	$u_{i,t}$	−0.27 (0.09)	0.00	$w_{i,t}$	−0.10 (0.04)	0.01
$w_{i,t}$	−0.16 (0.04)	0.00	$u_{i,t-1}$	−0.33 (0.10)	0.00	$w_{i,t-1}$	0.09 (0.04)	0.02
$k_{i,t}$	0.26 (0.03)	0.00	pr_{it}	0.29 (0.06)	0.00	$pop_{i,t}$	0.48 (0.09)	0.00
$\Delta k_{i,t}$	0.82 (0.19)	0.00	b_t	0.27 (0.07)	0.00	$\Delta pop_{i,t}$	0.51 (0.28)	0.07
oil_t	−0.02 (0.007)	0.00						
tax_t	−1.15 (0.30)	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; Δ denotes the difference operator.

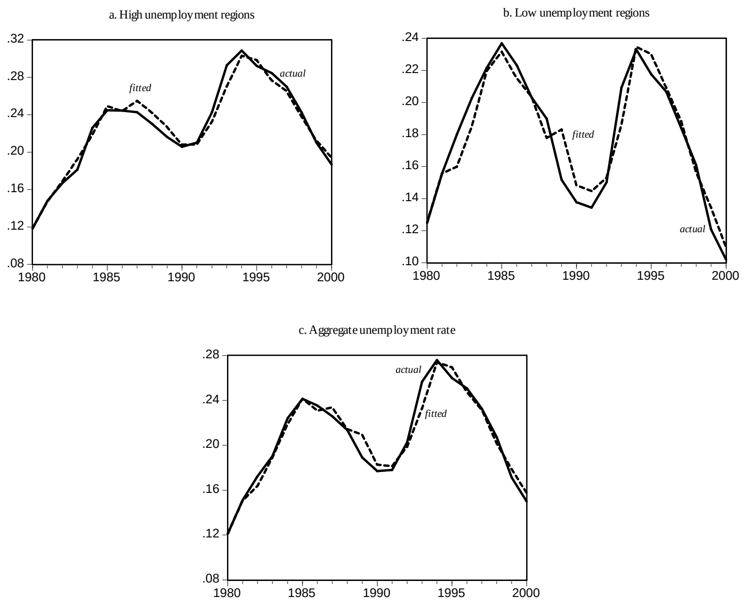
MLL is the maximum log likelihood; S.C.. is the Schwarz information criterion.

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

It is important to point out that a salient feature of the above estimations is that a major determinant of the unemployment rate is the size of capital stock both in the short and long run. This is in sharp contrast to the influential single-equation unemployment literature, which, on the basis of the observation that the unemployment rate is trendless, asserts that policies that shift upward the time path of capital stock have no long-run effects on the unemployment rate (Layard et al., 1991), or that the unemployment rate may depend on trendless transformations of the capital stock (for example, the capital labour ratio). However, Karanassou and Snower (2004) argue that there is no reason to believe that the labour market alone is responsible for ensuring that the unemployment rate is trendless in the long run.[28] Since equilibrating mechanisms in the labour market and other markets are jointly responsible for this phenomenon, the unemployment rate should not be required to be invariant to capital stock movements. Instead, 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 to ensure the trendless property of unemployment in the long run.[29]

Figure 3 shows that the univariate representation of the unemployment rate derived by the fitted values of our system of equations tracks the trajectory of the actual unemployment rate very closely. In the following section we seek to investigate the role played by the interplay of lagged adjustment processes and shocks in the the trajectory of the unemployment rate, and evaluate the contributions of the changes in the exogenous variables to its evolution.

Figure 3. Actual and fitted values



[28] We should note that the significant influence of capital stock on unemployment is an empirical fact unveiled by CRT studies for the UK (Henry et al., 2000; Karanassou and Snower, 2004), the EU (Karanassou et al., 2003), the Nordic countries (Karanassou, et al., 2008), Spain (Bande and Karanassou, 2009; Karanassou and Sala 2009a), and Australia (Karanassou and Sala 2010).

[29] For example, in the context of the illustrative labour market model (5), (6), (7) and (8), the restriction for a trendless unemployment rate is

$$\begin{aligned}(1-\alpha_2)\,\beta_1\Delta k^{LR} &= (1-\alpha_1)\,(1-\alpha_2)\,\beta_3\Delta z^{LR} \\ &\quad + [(1-\alpha_1)\,\gamma_3\beta_2+\gamma_1\beta_2]\,\Delta x^{LR},\end{aligned}$$

where $\Delta(\cdot)^{LR}$ denotes the long-run growth rates of the right-hand side variables.

5 Unemployment Contributions of the Exogenous Variables

5.1 Conceptual Underpinnings

Another characteristic of our dynamic modelling approach is that we define an impulse, or shock as a one-off change in a specific exogenous variable. Defining a shock (impulse) as a change in an exogenous variable, rather than as a one-off change in the residuals of a behavioural equation, has a clear advantage: it gives rise to dynamic 'contributions', a measure that shows how the endogenous variable of a dynamic equation responds to the actual changes in an exogenous variable over a sample interval.

The most pedagogical illustration of the concept of dynamic contributions can be given in the context of a simple AR(1) unemployment rate equation:

$$u_t = \alpha u_{t-1} + \beta x_t, \text{ where } |\alpha| < 1. \tag{16}$$

The impulse response function (IRF) of the stochastic process (16) to a one-off unit change in the exogenous variable x_t is

IRF of the AR(1):

time	t	$t+1$	$t+2$	...	$t+10$	...
responses	β	$\beta\alpha$	$\beta\alpha^2$	...	$\beta\alpha^{10}$	...

. (17)

Note that a one-time unit shock will have an immediate unit$\times\beta$ impact on unemployment, while the future effects of the shock decline in a geometric fashion. We can summarise the sensitivity of the unemployment rate with respect to variable x as:

$$\underset{\beta/\left(1-\alpha\right)}{\text{long-run sensitivity}} = \underset{\beta}{\text{short-run sensitivity}} + \underset{\beta\alpha/\left(1-\alpha\right)}{\text{persistence}}, \tag{18}$$

where unemployment persistence is defined as the sum of future responses, i.e. the responses in the aftermath of the shock, short-run sensitivity refers to the contemporaneous response, and the long-run sensitivity is given by the sum of all responses.

On the basis of the above analysis, we measure the contributions of the exogenous variable x to the evolution of employment over a specific period of time , say $t = 1$ to $t = T$, by sequentially adding up the IRFs of the respective changes during the specific period. Let $\Delta x_j = x_j - x_{j-1}$, where $j = 1, 2, ...T$, and Δ is the first difference operator. The IRFs of these T shocks are:

$$\begin{bmatrix} & t=1 & t=2 & ... & t=T \\ \text{IRF}_1: & R_{11} & R_{12} & ... & R_{1T} \\ \text{IRF}_2: & - & R_{22} & ... & R_{2T} \\ ... & - & - & ... & ... \\ \text{IRF}_T: & - & - & ... & R_{TT} \end{bmatrix}, \tag{19}$$

where IRF_j denotes the response function of employment to the jth shock, and R_{jt} is the response to shock j in time t. Note that the diagonal elements in matrix (19) denote the respective contemporaneous employment response to the jth one-off shock, whereas the elements above the diagonal denote the employment responses in period t to the shocks which occured in the past j periods. Therefore, the t-period contribution can be obtained as the sum of all responses in this period.

In other words, the contributions of the exogenous variable x to the unemployment trajectory for the given interval are given by the following time series:

$$\begin{array}{ccccc} t=1 & t=2 & t=3 & ... & t=T \\ R_{11}, & \sum_{j=1}^{2} R_{j2}, & \sum_{j=1}^{3} R_{j3}, & ... & \sum_{j=1}^{T} R_{jT}. \end{array} \tag{20}$$

5.2 Results and the Role of Capital Accumulation

It is clear from Figure 2 that the evolution of the unemployment rate is characterised by three turning points (1985, 1991, and 1994): it starts decreasing in 1985 until 1991, then increasing until 1994, and again decreasing after that point. Consequently, we are interested in measuring how each of the exogenous variables contributed to the trajectory of the unemployment rate during the booming periods of the second half of the eighties and the second half of the nineties, and the recession years of the early nineties. Figure 4 plots the evolution of the exogenous variables in our labour market model and highlights the three periods of interest.

For each group of regions we examine the influence of the exogenous variables on the unemployment time path over the periods 1985-1991, 1991-1994, and 1994-2000 by carrying out counterfactual simulations and applying the technique described in the previous section.[30] We evaluate the contributions of a given exogenous variable, say x, over a specific period by plotting the actual series of unemployment against its simulated series obtained by fixing, in the estimations of Tables 5 and 6, the exogenous variable x at its value in the start of the specific period (the dotted lines in Figure 4) and dynamically solving the resulting model.[31]

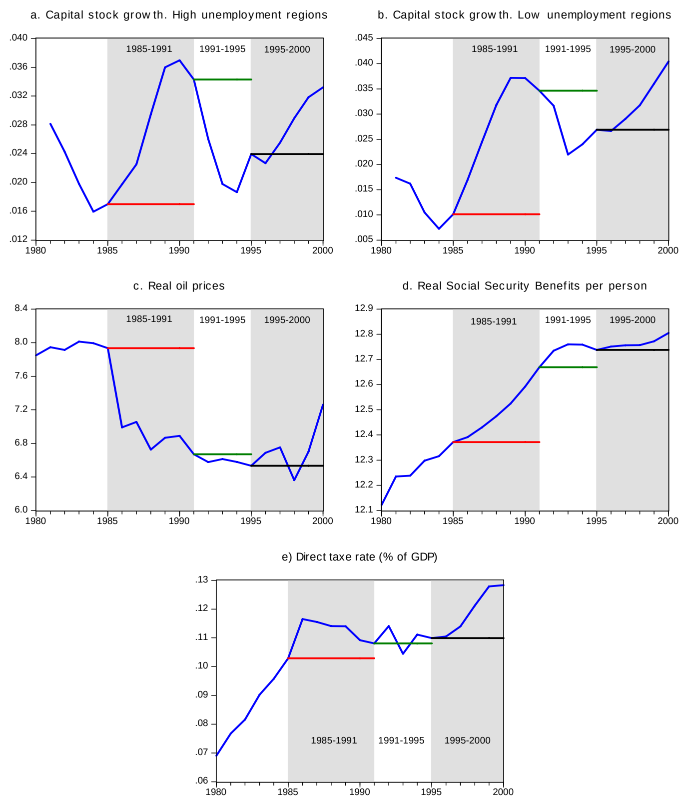
Figures 5, 6, and 7 plot the simulated versus the actual unemployment rates over the periods 1985-1991, 1991-1994, and 1994-2000, respectively. The distance between the actual (solid lines) and simulated (dotted lines) series measures the dynamic contributions of the exogenous variable x to uemployment for the specific period: panels a, b, c, and d show the contributions of investment, oil prices, benefits, and direct taxes, respectively. The simulated series represents the trajectory of the unemployment rate in the absence of any changes in x after the start of a specific period, and in the presence of all other shocks during that period. Consider, for example the contributions of investment to the high and low unemployment groups over the 1985-1991 period (see Figure 5a). Our dynamic accounting exercise answers to "Had capital stock growth remained as low as 1.8%, i.e. at its 1985 value, what would have been the unemployment rate

[30] We only evaluate the contributions of (i) investment, which is the main growth driver, (ii) oil price shocks, since these are typically examined in a wide spectrum of models, and (iii) benefits and taxes, as these are among the main determinants of the NRU. To save space, the results on working age population, which were found to have a rather minor influence on the unemployment trajectory, are available upon request.

[31] It is important to note that this is simply a dynamic accounting exercise, answering the question 'how much of the movement in unemployment can be accounted for by the movements in each of the exogenous variables' - it does not tell us what unemployment would have been had the exogenous variables followed different time paths.

in 1991?" An outline of our results follows; note that for simplicity we refer to investment as the growth rate of capital stock, i.e., we use the two terms interchangeably.[32]

Figure 4. Exogenous variables in the empirical model



During the 1985-1991 boom period, investment (i.e. the growth rate of capital stock) and oil prices were the main factors causing the downward trend in unemployment. By 1991, the increase in investment contributed to a decrease in the unemployment rate of the high (low) unemployment regions by approximately 7 (13) percentage points, pp. (Figure 5a). In addition, the reduction of oil prices after the mid eighties also contributed to the unemployment decrease in the high (low) unemployment regions by 4 (8) pp. (Figure 5b). On the other hand, the rising benefits contributed by putting upward pressure on unemployment; had benefits not increased in the second half of the eighties, the unemployment rate in the high (low) group of regions would have been lower by 3 (1) pp. (Figure 5c). Moreover, taxes were responsible for an increase of 3 pp (6) in the unemployment rate (Figure 5d).

During the 1991-1994 recession, the contribution of investment in the unemployment rate of the high (low) group of regions was an increase of around 7 (3) pp. (Figure 6a). In turn, Figures

[32] We should point out that investment is the dominant factor in the evolution of capital stock growth for modest depreciation rates. This can be seen from the following equation in levels:

$$K_t = K_{t-1} + I_t - \delta K_{t-1},$$

where δ is the depreciation rate and I_t is investment, and K_t is capital stock (in levels). Thus, in exact terms, the growth rate of capital stock equals investment (normalised by lagged capital) minus the rate of depreciation: $\frac{K_t - K_{t-1}}{K_{t-1}} = \frac{I_t}{K_{t-1}} - \delta$. Nevertheless, the fact that the essence of capital stock growth is reflected in investment justifies the alternate reference to the two magnitudes.

6b-d show that the unemployment contributions of oil prices were, as expected, minimal after 1991 when oil prices stabilised at relatively low levels, and the effects of benefits and taxes were also quite small.

Once again, during the 1994-2000 boom years, investment was the main contributor to the unemployment reduction (Figure 7a). Specifically, had capital stock growth remained at its 1994 level, the unemployment rate in the high (low) unemployment group would have been 26% (15%) instead of the actual 19% (10%). Regarding the rest of the exogenous variables (national or regional), Figures 7b-d show that they did not play such a significant role.

Overall, our results show that capital accumultion has been the main driving force of the unemployment rate ups and downs from 1985 to 2000. These regional findings are in line with the aggregate results obtained by Karanassou and Sala (2009a) for the Spanish economy over the 1970-2005 period.

Finally, we should note the asymmetric pattern of the gain/loss effects in the relative unemployment rates of the two groups over the horizon under examination. In the boom years 1985-1991 and 1994-2000, the low unemployment rate group benefited by around 1.5 times more than the high unemployment group of regions due to the increase in capital accumlation. In contrast, during the recession years 1991-1994, the high unemployment regions were hit by around twice as much as the low unemployment regions due to the slowdown in investment.

Figure 5. Unemployment Contributions: 1985-1991

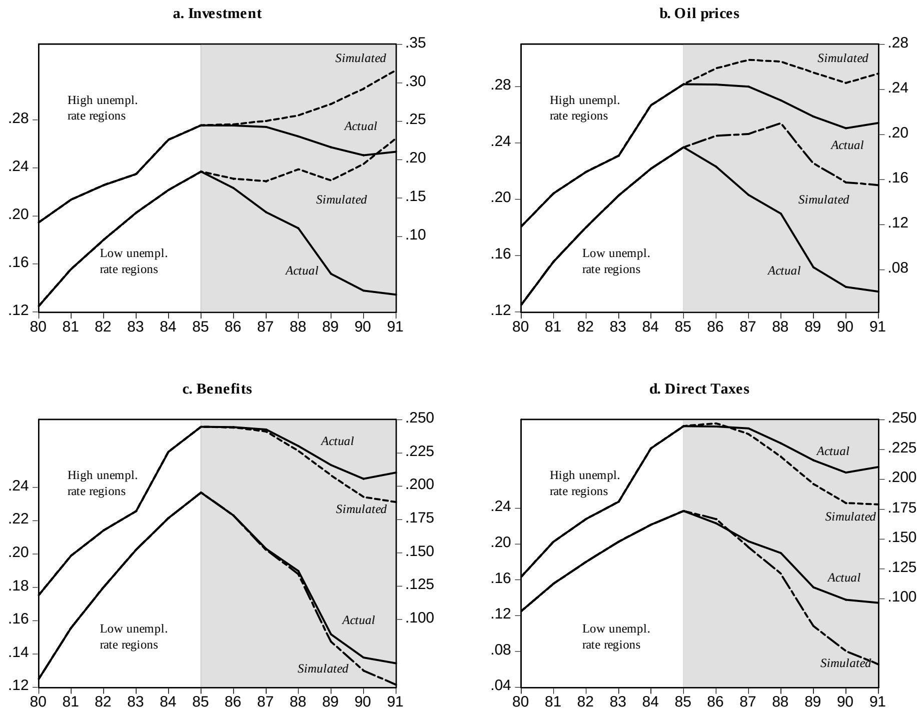


Figure 6. Unemployment Contributions: 1991-1994

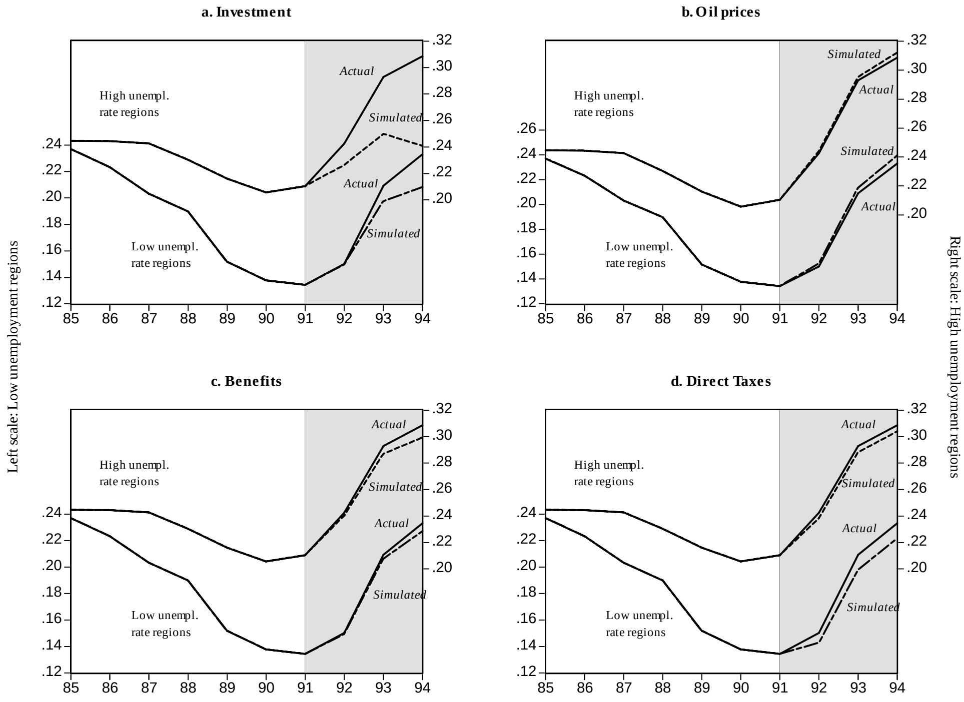
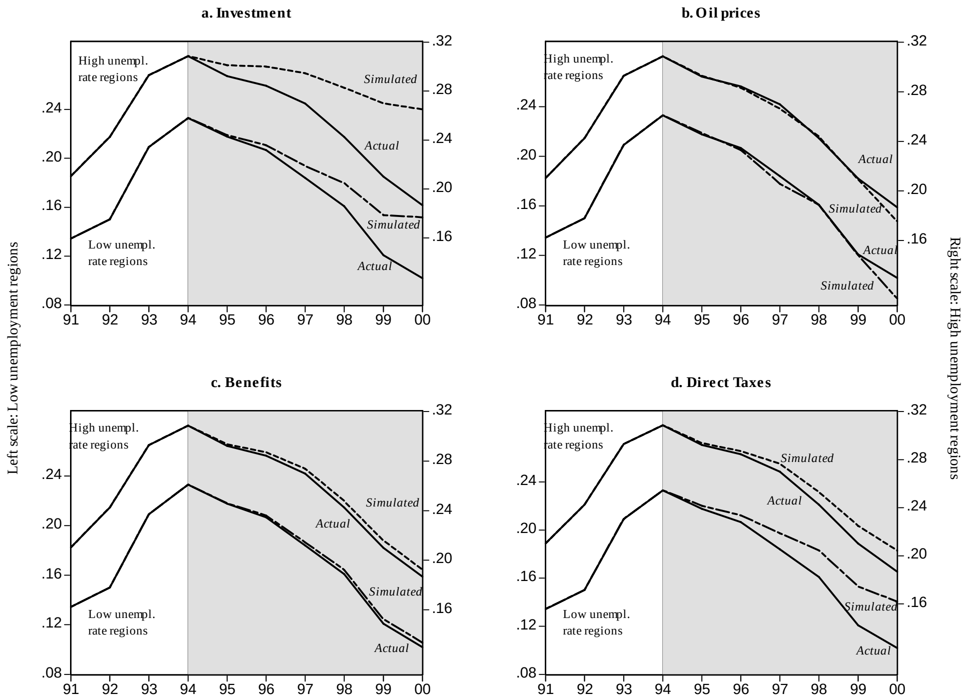


Figure 7. Unemployment Contributions: 1994-2000



6 Conclusions

This paper provides a rigorous account of the evolution of regional unemployment disparities in Spain over the 1985-91, 1991-94, and 1994-2000 periods. Using kernel densities and cluster analysis, we identified a high relative unemployment group of ten regions and a low unemployment group of seven regions, and then investigated the determinants of their unemployment rates and evaluated regional disparities. Spain represents a particularly interesting case within Europe, since it combines high aggregate unemployment with substantial regional differences. In particular, while some regions were close to full employment during the nineties, others experienced severe and persistent high unemployment for several decades. The analysis of the Spanish case may, thus, shed light into the determinants of regional unemployment dynamics in other European countries.

Our contribution to the existing literature has been twofold. First, we presented an analysis of the workings of the chain reaction theory of unemployment and argued that structural labour market models, comprising labour demand, wage setting, and labour force equations, allow for a richer interpretation of regional unemployment rates than the conventional reduced-form unemployment equations. This is because the interactive dynamic models of the CRT approach view the evolution of unemployment rates at a regional level as the interplay of lagged adjustment processes and shocks, where "shocks" refer to changes in the exogenous variables of the model. Since different regions may be exposed to different types of shocks and experience different adjustment processes, our CRT model provides a novel approach for explaining regional unemployment disparities.

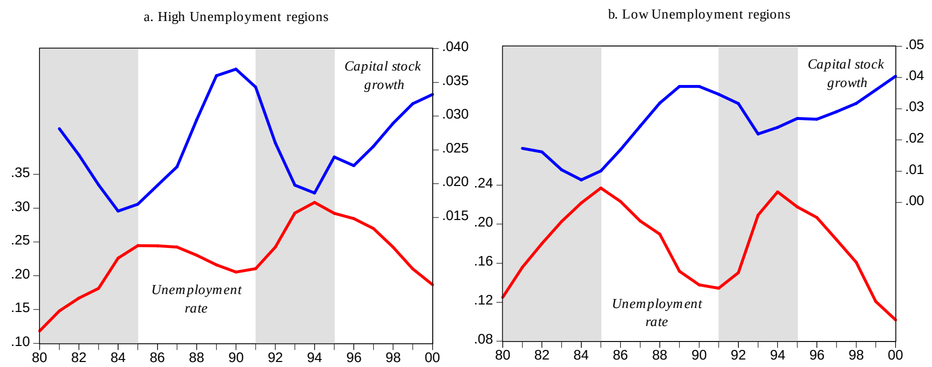
Second, our empirical findings demonstrated that capital accumulation is the magor driving force of unemployment. This is not surprising - as pictured in Figure 8, there is a profound negative relationship between capital stock growth and the high/low unemployment groups of regions examined in this paper. We should note that our empirical findings are in accordance with the aggregate results obtained by Karanassou and Sala (2009a) for the Spanish economy over the 1970-2005 period. Furthermore, our results reinforce the finding of Bande and Karanassou (2009) that in "good" times the low unemployment group of regions benefits more than the high unemployment one, whereas in "bad" times the high unemployment group of regions is hit more severely than the low unemployment one.

One lesson drawn from our study is that policy makers should take into account the idiosyncratic timing and intensity of regional unemployment responses to labour market shocks, especially if the policy aims at reducing the unemployment differentials among regions. Therefore, different policies should be applied to the high and low unemployment groups of regions in order to reduce regional unemployment disparities. This is in line with the recommendations made by Overman and Puga (2002).

Our results open new questions that need to be addressed in future research. First, if investment is interest-rate driven, or influenced by monetary policy decisions, we should investigate the role of monetary policy in explaining regional disparities, as in Carlino and De Fina (1998). There is evidence that monetary policy may exert different effects on regional economic activity, through different monetary policy transmission channels. While it has been shown by various authors, at the aggregate level, that the European Monetary Union is not an optimal monetary area (one size does not fit all), the argument is reinforced by the existence of significant regional disparities. These make it less plausible that shocks are symmetric (even within EMU countries), one of the preconditions for an optimal monetary area.

Second, if during the last decades investment has been responsible for such asymmetries in the labour market, we are sceptical as to whether the EU funding policy has been properly directed towards the right regions and/or the right targets. A recent work shows that structural EU funds have not reduced significantly the degree of regional labour market disparities (Bande et al., 2010a). Our findings offer an interpretation of this result: structural funds were mainly channeled to public investment in infrastructures, and the less developed regions (roughly the high unemployment ones) show a lower long-run elasticity of unemployment with respect to capital stock. Therefore, the impact of investment in these regions in terms of employment creation is smaller than in the more developed ones (note that in the group of low unemployment regions there were some Objective 1 regions, main recipients of the EU structural funds). In sum, it seems that this spending has not shortened the distance between the two groups of regions.

Figure 8
Capital stock growth (right scale) and unemployment rate (left scale)
High and Low unemployment regions



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