Analysing labor market flexibility using a semiparametric panel data model

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Abstract

Given the constrains imposed by European Monetary Union membership, flexibility in the labor market is crucial for countries and regions belonging to it. The paper addresses this issue empirically and analyses the real wage flexibility in Spain over the 1985-1999 period. Previous studies have examined wage flexibility by means of parametric methods. However, this paper analyses it within the framework of a semiparametric panel data model. The results point to a high degree of wage rigidity in Spain, because national and regional wage setting are closely linked. However, semiparametric estimation allows us to find some signs of flexibility; first, wages respond to regional unemployment rate growth for high levels of regional productivity growth; second, productivity increases at regional level have positive effects on wage growth, especially when regional unemployment growth is negative.

Keywords: Wage flexibility, unemployment rate, productivity, regions, European Monetary Union.

JEL code: C14, J30
1. – Introduction

The recent creation of the European Monetary Union (EMU) is one of the most important economic events for European countries. Nevertheless, its establishment brings about concomitant costs and benefits, which have been extensively analysed by the Optimum Currency Areas approach (OCA) (see e.g. Tavlas, 1993; Bayoumi and Eichengreen, 1996; Lafran y St-Amant, 1999; and Maza, 2004).

The OCA theory, though, has concentrated on the cost side of the cost-benefit analysis of a monetary union. According to this theory, the main cost of joining a monetary union is the abandonment of the exchange rate as an adjustment mechanism in response to shocks. However, it has been proved that this cost depends on two conditions: a) the probability of suffering asymmetric shocks (Maza, 2002) and; b) the lack (or presence) of alternative adjustment mechanisms to exchange rate in order to reduce the harmful effects of this kind of shocks. The OCA theory has demonstrated that the loss of the exchange rate instrument through the introduction of a single currency narrows the scope for governments that wish to address adverse economic shocks (see e.g. Carporale, 1993). The lack of this familiar policy instrument shifts the focus towards wage flexibility as a mean of coping with asymmetric shocks.

For this reason, among others, several papers have analysed wage flexibility using econometric techniques (to be precise, estimating a wage equation), both in Europe (see e.g. Abraham et. al., 2000) and in Spain (see e.g. Bajo et. al. 1999; Villaverde and Maza, 2002). On this topic, the evidence points to a limited wage flexibility.

Previous studies have a common characteristic: the use of a parametric approach. Therefore, it is assumed that the relationship among the endogenous variable (real wages) and the exogenous variables in the regression equation is parametric -linear in most cases. Notwithstanding,
more recent econometric theory challenges this view; the new approach – both nonparametric and semiparametric methods (see Hardle et. al., 1999) - allows more flexibility in the functional relationship among variables. So, this paper uses the Spanish case as a sort of laboratory for the analysis of real wage flexibility applying semiparametric techniques to a panel data set.

The structure of the paper is as follows. A brief image of the situation of the Spanish labour market is shown in section 2. The semiparametric panel data model is presented in section 3. Section 4 develops an empirical analysis of the regional wage flexibility in Spain. Finally, the main conclusions are presented in section 5.

2. – The situation of the Spanish labour market

The aim of this section is to briefly give an overview of the recent developments of the labour market in Spain. To do that, we make use of wages, unemployment rates and productivities data at regional level for the years 1985 through 1999 –a regional panel data set of the 17 Spanish regions- provided by the Fundación de las Cajas de Ahorros Confederadas (FUNCAS). Wages (productivities) are calculated as the ratio between labour costs (gross added value) and number of employees.

Some justification for the choice of the data bank is mandatory. The main reason for the Spanish case to be analysed in this paper is that, although the high unemployment rates are the main economic problem in Europe, Spain is the country where the situation of the labour marker is more worrying (Jimeno y Bentolila, 1998). In addition, and though our data bank is not certainly free of problems, it has an advantage front to others: the series are carefully constructed and fully comparable across regions and over time.

Table 1 presents regional differences for the variables used in this study (taking national mean equal to 100). Three alternative inequality indicators
are computed (standard deviation, variation coefficient and Theil index) and their results are very similar. All of them point at a same picture regarding inequality at regional level in wages, unemployment and productivity. However, the most remarkable feature of these results is the great difference between the inequality indicators computed on wages and unemployment rates. Inequality seems to be much lower among regional wages —and productivities— than among regional unemployment rates. In addition, inequality indicators have decreased both for wages and productivities in the period under study while, in the same time, these indicators have increased for unemployment rates. Accordingly, the results point to a high degree of wage rigidity, with wages showing a weak responsiveness to the situation of the labour market, at least to unemployment rates; however, the inequality indicators seem to show that the evolution of regional wages could be affected to a certain extent by labour productivity growth.

Summing up, this section reflexes two interesting aspects of the Spanish labour market. First, the existence of external wage-homogenising factors, because inequality on wages has got lower and lower in the period over study. It is one of the objectives of this paper to more fully understand the factors provoking this particular situation. Second, wage growth seems to be independent of the evolution of regional unemployment rates. This question will be also analysed in the next sections.

3. – A semiparametric panel data model

As it has been pointed out in the introduction of this paper, within the statistical framework of panel data most part of the studies has devoted to the specification and estimation of a fully parametric model (see e.g. Hsiao, 1986; Baltagi, 1995; Arellano and Honoré, 2001). However, sometimes there is no reason to assume the existence of a parametric relationship among variables. For this reason, nonparametric approach arises. This technique is based on the belief that parametric models are usually misspecified and may result in incorrect inferences (see e.g.
Robinson, 1983; Hardle and Linton, 1994; Porter, 1997; Lee and Kondo, 2002). The goal of nonparametric models is the achievement of more flexible and robust models, because this kind of models does not impose a functional form of the regression to be estimated. However, nonparametric estimation has also some drawbacks. The main problem of this estimation technique is the so-called “curse of dimensionality”, because nonparametric estimators are based on the idea of local (weighted) averaging. In high dimensions the observations are normally sparsely distributed for reasonable sample sizes and, thus, estimators based on local averaging perform unsatisfactorily.

In addition, purely nonparametric models have also two weak points. First, it is possible to know some information about the model and if we know, for instance, that there is a linear relationship between an explanatory variable and the dependent variable, a flexible form of the function to be estimated would not be necessary; and second, nonparametric approach requires some kind of smoothness, and this is not possible if we work with discrete explanatory variables.

Therefore, both parametric and nonparametric models present several drawbacks. For this reason, semiparametric approach emerged in the late 80’s (Robinson, 1988). Semiparametric techniques keep the main advantage of parametric models –the easy interpretation of the results, but, at the same time, give more flexibility in some aspects of the model (see e.g. Li and Stengos, 1996; Li and Hsiao, 1998; Chen, Heckman and Vytlacil, 1998; Baltagi and Li, 2002).

Bearing these arguments in mind, let us consider a semiparametric panel data model. Semiparametric approach combines two elements; one of them must be estimated nonparametrically while the other requires the estimation of a set of finite dimensional parameters. Semiparametric models can be interpreted as a sum of a purely parametric part, $X_{it} \beta$, and a purely nonparametric part, $\eta(Z_{it})$. The general form of these models is:
\begin{align*}
Y_{it} &= X_{it} \beta + \eta(Z_{it}) + \epsilon_{it} \quad \text{for } i=1,\ldots,n, \ t=1,\ldots,T \tag{2.1}
\end{align*}

where $X_{it} = (X_{it1}, \ldots, X_{itp})$ and $Z_{it} = (Z_{it1}, \ldots, Z_{itd})$ are vectors of explanatory variables of dimension $p$ and $d$ respectively. Concretely, $X_{it}$ is the vector of variables with a linear influence on the endogenous variable $(Y_{it})$ and $Z_{it}$ is the vector of the rest of explanatory variables with an unknown influence on $Y_{it}$. In addition, $\beta$ is the vector of parameters linked to $X_{it}$, and $\eta(.)$ is an unknown multivariate nonparametric function of $Z_{it}$. Finally, the error term $\epsilon_{it}$ is assumed to be i.i.d. with zero mean.

For the estimation of equation (2.1) we must take into account that its conditional expectation is:

\[ E(Y_{it}|Z_{it} = z_{it}) = E(X_{it}|Z_{it} = z_{it})\beta + \eta(Z_{it}) + E(\epsilon_{it}|Z_{it} = z_{it}) \tag{2.2} \]

and we know that $E(\epsilon_{it}|Z_{it} = z_{it}) = 0$. Then, subtracting (2.2) from (2.1) we obtain

\[ \tilde{Y}_{it} = \tilde{X}_{it} \beta + \epsilon_{it} \tag{2.3} \]

where $\tilde{Y}_{it} = Y_{it} - E(Y_{it}|Z_{it} = z_{it})$ and $\tilde{X}_{it} = X_{it} - E(X_{it}|Z_{it} = z_{it})$. Now, we can estimate the vector of parameters $\beta$. Using equation (2.2), we can express the multivariate nonparametric component in the following way:

\[ \eta(Z_{it}) = E(Y_{it} - X_{it} \beta|Z_{it} = z_{it}) \tag{2.4} \]

Hence, according to (2.3) and (2.4), the steps in the estimation procedure of $\beta$ and $\eta(.)$ are the following:
**First step:** Estimating \( E(Y_{it}|Z_{it} = z_{it}) \) and \( E(X_{it}|Z_{it} = z_{it}) \) for the \( p \) explanatory variables included in the parametric part by means of a nonparametric method

\[
E(Y_{it}|Z_{it} = z_{it}) = m(z_{it}) = m(z_{it1}, \ldots, z_{itd})
\]

\[
E(X_{it}|Z_{it} = z_{it}) = g(z_{it}) = g(z_{it1}, \ldots, z_{itd})
\]

The nonparametric regression estimator for the multivariate function \( m(.) \) is:

\[
\hat{E}(Y_{it}|Z_{it} = z) = \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=1}^{T} \frac{1}{h_{d}} \textbf{K}(Z_{it} - z) Y_{it}
\]

(2.5)

where \( \textbf{K} \) is a multivariate kernel function \((\textbf{K} : R^d \rightarrow R)\) and \( \hat{\rho}(z) \) is the kernel density estimator to the \( d \)-dimensional case

\[
\hat{\rho}(z) = \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=1}^{T} \frac{1}{h_{d}} \textbf{K}\left(\frac{Z_{it} - z}{h}\right) = \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=1}^{T} \frac{1}{h_{d}} \textbf{K}\left(\frac{Z_{it1} - z_{i1}}{h_{i1}}, \ldots, \frac{Z_{itd} - z_{id}}{h_{id}}\right)
\]

(2.6)

Note that (2.5) and (2.6) assume that the bandwidth \( h \) is the same for each component. It is convenient to relax this assumption. Then, we have a vector of bandwidths \( h = (h_{i1}, \ldots, h_{id}) \), and the multivariate kernel estimators for the regression and density become

\[
\hat{m}_{h}(z) = \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=1}^{T} \frac{1}{h_{d}} \textbf{K}\left(\frac{Z_{it1} - z_{i1}}{h_{i1}}, \ldots, \frac{Z_{itd} - z_{id}}{h_{id}}\right) Y_{it}
\]

(2.7)

and
Thus, inserting (2.8) into (2.7) we get

\[
\hat{m}_h(z) = \frac{1}{nT} \sum_{i=1}^n \sum_{t=1}^T \frac{1}{h_1 \ldots h_d} K \left( \frac{Z_{it1} - z_1}{h_1}, \ldots, \frac{Z_{itd} - z_d}{h_d} \right) \left( \frac{Z_{it1} - z_1}{h_1}, \ldots, \frac{Z_{itd} - z_d}{h_d} \right)^T Y_{it} \]

(2.9)

Additionally, and although the multidimensional kernel function \( K(z) = K_1(z_1, \ldots, z_d) \) can present different forms, we use, for simplicity, a multiplicative kernel

\[
K(z) = K_1(z_1) \cdot \ldots \cdot K_d(z_d)
\]

In this case (2.9) turns out to be

\[
\hat{m}_h(z) = \frac{1}{\sum_{i=1}^n \sum_{t=1}^T \prod_{j=1}^d h_j^{-1} K_j \left( \frac{Z_{ij} - z_j}{h_j} \right)} \left( \frac{Z_{ij} - z_j}{h_j} \right) Y_{it} \]

(2.10)

where \( K_j(\cdot) \) is a one-dimensional kernel function \( K : R \to R \) for \( j = 1, \ldots, d \).

Then, the nonparametric regression function \( g(\cdot) \) is

\[
\hat{E}(X_{it}|Z_{it} = z) = \hat{g}_h(z) = \frac{1}{\sum_{i=1}^n \sum_{t=1}^T \prod_{j=1}^d h_j^{-1} K_j \left( \frac{Z_{ij} - z_j}{h_j} \right)} \left( \frac{Z_{ij} - z_j}{h_j} \right) \]

(2.11)
Second step: Using the nonparametric estimators, we can generate the following variables

\[
\tilde{Y}_{it} = Y_{it} - \hat{E}(Y_{it} | Z_{it} = z_{it})
\]

\[
\tilde{X}_{it} = X_{it} - \hat{E}(X_{it} | Z_{it} = z_{it})
\]

Third step: As a result, we have the regression function \( \tilde{Y}_{it} = \tilde{X}_{it} \beta + \epsilon_{it} \). Therefore, the estimator of the vector of parameters \( \beta \) is

\[
\hat{\beta} = \left( \sum_{i=1}^{n} \sum_{t=1}^{T} \tilde{X}_{it} \tilde{X}_{it}' \right)^{-1} \sum_{i=1}^{n} \sum_{t=1}^{T} \tilde{X}_{it} \tilde{Y}_{it}
\]  

(2.12)

Fourth step: With the estimation of \( \beta \), we can generate the variable

\[
\hat{Y}_{it} = \left( Y_{it} - X_{it} \hat{\beta} \right)
\]

Fifth step: Finally, we consider the equation \( \hat{Y}_{it} = \eta(Z_{it}) \); the nonparametric estimator of \( \eta(z) \) is

\[
\hat{\eta}_h(z) = \frac{\sum_{i=1}^{n} \sum_{t=1}^{T} \left[ \prod_{j=1}^{d} h_j^{-1} K_j \left( \frac{Z_{ij} - z_j}{h_j} \right) \right] \hat{Y}_{it}}{\sum_{i=1}^{n} \sum_{t=1}^{T} \left[ \prod_{j=1}^{d} h_j^{-1} K_j \left( \frac{Z_{ij} - z_j}{h_j} \right) \right]}
\]  

(2.13)

Provided the estimation method, we can applied it to several contexts. In the next section we present an application of this technique for the analysis of Spanish labour market.

4. – An empirical analysis of wage flexibility in Spain
As an example of the utility of the previous section model, and in order to analyse wage flexibility in Spain, we have estimated the following equation, which can be derived from a model of wage bargaining between unions and employers as in Abraham (1996):

\[
\hat{\omega}_{it} = \beta_1 \hat{\omega}_t + \beta_2 \hat{u}_{it} + \eta(\hat{u}_{it}, \hat{\lambda}_{it}) + \varepsilon_{it}
\]  

(3.1)

According to this equation, the real wage growth in region \( i \) and period \( t \) (\( \hat{\omega}_{it} \)) depends on the average of the national wage growth (\( \hat{\omega}_t \)), the national and regional unemployment rate growth (\( \hat{u}_t, \hat{u}_{it} \)) and the regional productivity growth (\( \hat{\lambda}_{it} \)). In this equation we suppose a linear relationship between the endogeneous variable and the national exogenous variables (\( \hat{\omega}_t, \hat{u}_t \)); however, regional unemployment rate growth (\( \hat{u}_{it} \)) and regional productivity growth (\( \hat{\lambda}_{it} \)) have unknown influence on \( \hat{\omega}_{it} \). So, the main added value of the estimation of equation (3.1) -compared to a traditional parametric estimation\(^1\) - is that the influence of regional unemployment and productivity on regional wages can be different according to their values.

The results of equation (3.1), using the estimation procedure that has been displayed in the previous section, are presented in Table 2 (parameters \( \beta_1 \) and \( \beta_2 \)) and Figure 1 (the multivariate nonparametric function \( \eta \) of \( \hat{u}_{it} \) and \( \hat{\lambda}_{it} \))\(^2\). We can summarize the main findings as follows:

1. The coefficient linked to national wage growth is 0.9 and results significant at 1% level, which shows that this variable exerts a

\(^1\) Parametric estimation is shown in the Appendix.
\(^2\) Concerning the goodness of fit of the regression the classical \( R^2 \) test is not feasible to a semiparametric case. For this reason, we have calculated it using the improved Akaike information criterion, since the original Akaike criterion was designed for parametric models. The modified version allows us to evaluate the precision of the estimation in semiparametric environments and to compare parametric and semiparametric estimation (Hurvich et. al, 1998; Simonoff and Tsai, 1999). Our results show that the semiparametric specification describes the data better than the parametric one.
strong influence on the evolution of regional wage. According to this result and what we mentioned in the first part of the paper, Spanish labour market does not seem flexible enough to absorb asymmetric shocks inside EMU.

2. Regional wage growth does not show a significant response to national unemployment rate growth. The coefficient associated with this variable is not statistically different from zero.

3. As Figure 1 shows, semiparametric estimation allows us to distinguish the effect of unemployment on wages depending on productivity growth values. In fact, this effect is ambiguous and it is conditioned to productivity growth. It seems that unemployment rate growth has only a strong negative effect on the evolution of wages for high levels of productivity growth, while this effect becomes null for low levels of it.\(^3\)

4. In relation to productivity, and in the same way, the results depend on unemployment growth. Figure 1 indicates that productivity increases have positive effects on wages for negative levels of unemployment growth; however, these effects are very weak when unemployment rate growth is high.\(^4\)

5. – Conclusions

This paper extends the model proposed by Abraham (1996) using a semiparametric panel data model in order to examine real wage flexibility at regional level in Spain. This approach allows us to combine desirable characteristics of parametric and nonparametric models.

\(^3\) The coefficient linked to unemployment rate growth in a parametric estimation is statistically equal to zero.

\(^4\) In this case, parametric estimation shows that the coefficient is 0.07 and is statistically significant at 5 per cent level.
After a descriptive study showing that regional wages are much more similar than regional unemployment rates, our semiparametric analysis points to a high degree of rigidity of regional wages. Regional wage growth setting is driven mainly by an attempt to homogenise it with respect to average national wage growth. Therefore, the Spanish labour market is characterized by regional wages which present a low responsiveness to the individual labour market situation.

On the contrary, a semiparametric analysis allows us to find and give some information about some signs of flexibility. First, the results indicate that, in certain situations, wages respond to an increase of unemployment in a strong negative way. To be precise, this fact occurs only when productivity growth is high. A possible interpretation of this aspect is that firms react to unemployment increases –decreasing their wages- only if potential labour force is better and better.

Second, labour productivity growth has a positive effect on the evolution of regional wages, especially when the economy is creating new jobs (unemployment rate growth is negative). It seems that only when the economic perspectives are good regional wages are certainly indexes to labour productivity.

In summary, and in spite of those hints of flexibility, we can assert that labour market in Spain is too rigid to respond by itself to asymmetric shocks. Policy implications of these results are obvious: measures intended to reinforce the link between wage growth and the labour market conditions of each area should be welcome in Spain to mitigate the costs of EMU.

References


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<td>1.36</td>
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Source: FUNCAS and own elaboration.
Table 2. Regional wage flexibility in Spain, 1985-1999

Dependent variable: \( \omega_{it} \)

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<th>Equation 3.1</th>
<th>Coefficients</th>
<th>Standard errors</th>
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<td>( \omega_t )</td>
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<td>( \tilde{\lambda}_{it} )</td>
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<td>Improved Akaike IC</td>
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Note: * denotes significance at 1% level. The symbol “n.p.v.” denotes nonparametric variables.
Source: FUNCAS and own elaboration.

Fig. 1: Bi-dimensional nonparametric function
**APPENDIX**

**Table A.1.** Regional wage flexibility in Spain, 1985-1999 (parametric estimation)

<table>
<thead>
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<th>Dependent variable: $\omega_{it}$</th>
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<th>Standard errors</th>
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<td>$\bar{u}_{it}$</td>
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<td>$\bar{\lambda}_{it}$</td>
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$R^2$ adjusted 0.916

Improved Akaike IC -0.119

Note: * denotes significance at 1% level. ** denotes significance at 5% level.

Source: FUNCAS and own elaboration.