Measuring job mismatch and structural unemployment in Portugal: An empirical study using panel data*

September 1996

Leonor Modesto

Universidade Católica Portuguesa
Palma de Cima
1600 Lisboa, Portugal
and
MINISTÉRIO DAS FINANÇAS

* Paper to be presented at OCDE meeting on "The NAIRU: Concept, Measurement and Policy Implications".
The present report is part of a project financed by the Ministry of Finance on Labour Market Developments.

Abstract

In this work we estimate a hiring function for the Portuguese economy using a panel of 36 professions for the years' 1984-95. We allow matching efficiency to vary across professions and in time, being able to construct two mismatch indicators. The first measures mismatch due to heterogeneity across professional labour markets. The other relates aggregate matching efficiency to institutional changes in the labour market, wage behaviour and the business cycle. We conclude that mismatch due to heterogeneity, although present, did not explain much of the observed unemployment rate. On the contrary, changes in aggregate matching efficiency were quite successful in explaining Portuguese labour market performance.

We find evidence of a stable long run Beveridge relation that is shifted in the short run by business cycle conditions. Moreover, we measured trend unemployment in Portugal and found that it did not increase during the last decade. Therefore, we can conclude that unemployment in Portugal seems to be mainly a cyclical phenomenon, and that recent changes in unemployment benefits do not seem to have worsen matching efficiency nor the Beveridge relation. Quite on the contrary, there is some evidence that seems to suggest an improvement in these fronts. It is however to soon to claim that this has happened.

1. Introduction

Unemployment is now one of the most pressing economic concerns in the majority of OECD countries. Moreover, in many countries the same levels of wage inflation, capacity utilisation and vacancy rates are now associated with higher levels of the unemployment rate than what used to be the case two decades ago. (See, e.g. Elmeskov and MacFarlan (1993)). This phenomenon reflects a rise in structural or trend unemployment, that has been explained by a rise in equilibrium unemployment and/or by a reduction in the speed of adjustment in labour markets. In Portugal, on the contrary, unemployment did not rise steadily in the last two decades, showing a marked cyclical pattern. Moreover, wages in Portugal seem to be much more flexible than in other European countries. Some authors (see Blanchard and Jimeno (1994)) suggested that in Portugal low unemployment benefits have led to a higher response of wages to unemployment. This in turn has led to less unemployment persistence. However, more recently, unemployment protection coverage increased. Therefore it seems important to see in what extent this changed the functioning of the labour market in Portugal i.e. to measure structural unemployment and isolate and discuss the factors responsible for its evolution.

In this work we obtain a measure of trend or structural unemployment in Portugal based on the Beveridge curve. We follow the framework proposed in Layard, Nickell and Jackman (1991, p. 324-326) introducing however some modifications following Entorf (1995). We start by estimating a hiring function using a panel of 36 professions for the years' 1984-1995. Using the obtained results we are then able to estimate both the Beveridge Curve and structural unemployment in Portugal.

The rest of the paper is organised as follows. In the next section we present the underlying theoretical framework. In section 3 we discuss the data and the estimation methods used and present the empirical results obtained. As explained above we then discuss the evolution of matching efficiency and construct the Beveridge curve. Structural unemployment is also obtained and its evolution is discussed and contrasted with the evolution of the observed unemployment and vacancy rates. Finally in section 7 we make some concluding remarks.

2. The Model

The Beveridge curve gives us an equilibrium relationship between unemployment and vacancies and is a useful tool for analysing the causes of unemployment. Most theories of the Beveridge curve start from postulating a hiring function. This function may be seen as a "production" function that transforms unemployed persons and vacant jobs into job matches. Previous research (see Blanchard and Diamond (1989) and also Layard et al. (1991)) suggests that this function is homogeneous of degree one.

Layard, Nickell and Jackman (1991) consider the following type of hiring function for sector i:

$$H_{it} = A_i V_{it}^{\alpha} U_{it}^{1-\alpha} \tag{1}$$

where $H_{it} = hirings\ in\ t\ of\ sector\ i$
$V_{it} = vacancies\ in\ t\ of\ sector\ i$
$U_{it} = unemployment\ in\ t\ of\ sector\ i$
$A_i = matching\ efficiency\ of\ sector\ i$

We will consider instead a hiring function of the type:

$$H_{it} = A_{it} V_{it}^{\alpha} U_{it}^{1-\alpha} \tag{2}$$

where $A_{it} = matching\ efficiency\ in\ t\ of\ sector\ i$

This means that we will allow matching efficiency to vary in time with the economic cycle and labour market conditions. More specifically we consider that:

$$A_{it} = A_i m(X_t) \tag{3}$$

where $X_t = vector\ of\ aggregate\ mismatch\ indicators.$

The variables to be considered in X_t are unemployment benefits, male and female participation rates, the minimum wage, the real wage and the business cycle.

Note that this specification is in the spirit of Entorf (1995) who considers:

$$H_{it} = A(X_t) V_{it}^{\alpha} U_{it}^{1-\alpha}. \tag{4}$$

Equation (2) will be estimated using panel data. This will give us more observations and will allow the coverage of sector movements. Moreover, this will enable us to construct a measure of aggregate matching efficiency that varies in time, $m(X_t)$, and to relate its behaviour both with the economic cycle and to changes in labour market institutional features.

On the basis of equation (1) Layard, Nickell and Jackman (1991) obtain an expression for the Beveridge curve in the following way:

Denoting the entry to unemployment in each sector by S_i and assuming that $S_i = s_i N_i$ where N is employment, then in the steady-state $S_i = H_i$ and we have that:

$$\frac{s_i}{A_i} = v_i^{\alpha} u_i^{1-\alpha}$$

where $v_i = \frac{V_i}{N_i}$

$$u_i = \frac{U_i}{N_i}.$$

This means that:

$$\sum f_i \left(\frac{s_i}{A_i}\right) = \left[\sum f_i \left(\frac{v_i}{v}\right)^{\alpha} \left(\frac{u_i}{u}\right)^{1-\alpha}\right] v^{\alpha}\, u^{1-\alpha} \qquad (5)$$

where $f_i = \dfrac{N_i}{N}$

$v = \dfrac{V}{N}$

$u = \dfrac{U}{N}$.

The term in brackets has a maximum value of unity when the U_i/V_i ratio is the same in all groups. At this point the aggregate unemployment rate is as low as it can be, for a given level of vacancies, and it is given by:

$$\log u^{*} = \frac{1}{1-\alpha} \log\left(\sum f_i \, \frac{s_i}{A_i}\right) - \frac{\alpha}{1-\alpha} \log v \qquad (6)$$

Note that expression (6) is also the aggregate Beveridge Curve that would have been obtained if the U_i/V_i ratios were the same in all groups.

Moreover from (5) we also have:

$$\log u^{*} = \log u + \frac{1}{1-\alpha} \log\left[\sum f_i \left(\frac{v_i}{v}\right)^{\alpha} \left(\frac{u_i}{u}\right)^{1-\alpha}\right] \qquad (7)$$

and ($\log u - \log u^{*}$) becomes a measure of mismatch. Indeed as the U_i/V_i ratios diverge the aggregate Beveridge Curve shifts out, i.e. unemployment is larger than it could be at given vacancies.

Similarly in our case we can from equation (2) obtain the Beveridge curve. Rewriting expression (2) in the following way:

$$H_{it} = A_i m(X_t) V_{it}^{\alpha} U_{it}^{1-\alpha} \qquad (8)$$

we have that:

$$\frac{H_{it}}{N_{it}} = A_i m(X_t) v_{it}^{\alpha} u_{it}^{1-\alpha}.$$

Therefore in the steady state:

$$\frac{s_i}{A_i} = m(X) v_i^{\alpha} u_i^{1-\alpha}$$

and we obtain:

$$\sum f_i \left(\frac{s_i}{A_i}\right) = \left[\sum f_i \left(\frac{v_i}{v}\right)^{\alpha} \left(\frac{u_i}{u}\right)^{1-\alpha}\right] v^{\alpha}\, u^{1-\alpha}\, m(X). \qquad (9)$$

This means that the minimum aggregate rate of unemployment is given by the following expression, which also describes the long run position of the Beveridge Curve if the U_i/V_i ratios were identical across groups:

$$\log u^* = \frac{1}{1-\alpha} \left\{\log\left(\sum f_i \frac{s_i}{A_i}\right) - \alpha \log v - \log m(X)\right\} \qquad (10)$$

Comparing expressions (10) and (6) we can see that the main difference between the two is that (10) can account for aggregate shifts in the Beveridge curve; i.e. if aggregate matching efficiency decreases or increases this affects the position of the Beveridge curve.

Moreover, as before, ($\log u - \log u^*$), given by expression (11) below, measures mismatch due to sector heterogeneity:

$$\log u - \log u^* = -\frac{1}{1-\alpha} \log\left[\sum f_i \left(\frac{v_i}{v}\right)^{\alpha} \left(\frac{u_i}{u}\right)^{1-\alpha}\right]. \qquad (11)$$

Therefore, the empirical observation that higher levels of unemployment are now associated with the same levels of vacancies, i.e. outwards shifts of the aggregate Beveridge Curve can be accounted for in this proposed framework by two alternative explanations: (i) a decrease in aggregate matching efficiency, that can be traced to changes in labour market institutions or legislation concerning its functioning, changes in the composition of labour supply or effects of search discouragement; and (ii) to increased mismatch due to sector imbalances.

3. Estimation

The equation to be estimated is the following:

$$\ln H_{it} = \ln A_{it} + \alpha \ln V_{it} + (1-\alpha)\ln U_{it} + e_{it} \qquad (12)$$

where:

$$\ln A_{it} = \ln A_i + a_1 BC_t + a_2 MPR_t + a_3 FPR_t + a_4 \ln WR_t + a_5 UB_t + a_6 r\min{}_t$$

and: *BC* = deviations of GDP from trend
MPR = male participation rate
FPR = female participation rate
WR = real wage
UB = unemployment benefits
rmin = minimum wage/average wage

3.1 The data

To estimate (12) we will use a panel for 36 professions over the period 1984-95.

Data sources:

The data for **vacancies**, **hirings** and **unemployment** comes from the monthly statistics published by the IEFP of the Portuguese Ministry of Employment. This data is collected on a monthly basis from the registers of the Employment Centres since the beginning of 1984 for 36 professional categories.

For the **aggregate unemployment rate** we considered two sources: (i) the IEFP administrative data on a monthly basis, and (ii) the quarterly Labour Force Survey (IE) of the Portuguese Statistical Institute (INE).

GDP comes from the national accounts of the Portuguese Statistical Institute (INE) and from the Annual Reports of the Bank of Portugal (BP). The variable **BC** is defined as the ratio between actual and trend GDP. Therefore a value above (below) unity indicates that GDP was above (below) trend in that year. Trend GDP was obtained assuming a linear trend for the log of GDP.

Participation rates are also obtained from the quarterly Labour Force Survey (IE).

Wages were obtained (i) from the National Accounts of the Portuguese Statistical Institute (INE) on a yearly basis and (ii) from the Portuguese Ministry of Employment, also on an annual basis. Average nominal wages were constructed dividing total earnings by the number of workers.

The **minimum wage** also comes from the Portuguese Ministry of Employment.

To deflate the wage series we used the **consumer price index** of the INE that is published monthly.

To measure the effects of **unemployment benefits** we constructed a set of dummy variables that take different values for periods with different regimes. Before 1985 unemployment benefits were almost non existent. In 1985 new legislation was produced and unemployment benefits were introduced. In the end of 1989, the rules governing the amount of the benefits, the period of coverage and eligibility were changed, becoming more friendly to the unemployed. Therefore we decided to consider two dummy variables, one for the period 1985-89 and another for the years' 1990-95.

In this work we estimate equation (12) using annual data. Initially we also had planned to estimate a quarterly version but, as we had problems in obtaining quarterly information for some of the aggregate variables, we decided to leave it for further research.

3.2 Estimation Methods

We can rewrite (12) as:

$$y_{it} = \eta_i + \sum_{k=1}^{K} \beta_k x_{kit} + e_{it} \qquad (13)$$

$$where\ \eta_i = \ln A_i$$

$$and\ i = 1,\dots,N\ and\ t = 1,\dots,T$$

i.e. slope coefficients are constant and the intercept can vary over groups.

A number of estimators are possible for (13). We consider the *OLS*, the *within* or fixed effects estimator and the *variance components* estimator.

The *within* estimator assumes that the η_i are fixed parameters and that the e_{it} are independent and identically distributed random variables with $E[e_{it}]=0$ and $E[e^2_{it}]=\sigma^2_e$. This estimator simply consists on applying OLS to deviations from group means. It provides consistent estimators of the β even when the x and the η_i are correlated. To obtain the fixed effect for each group one applies (14):

$$\hat{\eta}_i = \overline{y_i} - \sum_{k=1}^{K} \hat{\beta}^w_k \overline{x_{ki}} \tag{14}$$

where $\overline{y_i}$ and $\overline{x_{ki}}$ are the group means of the dependent variables and the regressors.

One major drawback of the within estimator is that it eliminates the possibility to identify time invariant effects. However, in our case this does not constitute a problem as we do not consider this type of effects.

If the intercepts are not different across groups and the other hypotheses of the model continue to hold, then there is no basis for differentiating the time-series
cross-sectional nature of the data, and, for estimation purposes the data can be treated as one sample of *NT* observations. This is equivalent to applying plain *OLS* estimators.

The *variance components* estimator is a GLS estimator that assumes that $\eta_i = \eta + \mu_i$ and that the μ_i are random variables with zero mean, constant variance σ^2_μ, and that $E[\mu_i \mu_j]=0$ for $i \neq j$. Moreover the μ_i are assumed to be uncorrelated with the e_{it}. This estimator results from applying OLS to the transformed model:

$$y_{it} - \theta\overline{y_i} = (1-\theta)\,\eta + \sum_{k=1}^{K} \beta_k\,(x_{kit} - \theta\overline{x}_{ki}) + v_{it} \tag{15}$$

with $\theta = 1 - \dfrac{\sigma_e}{\sigma_1}$ and $\sigma^2_1 = T\sigma^2_\mu + \sigma^2_e$

and where the v_{it} are homoscedastic and uncorrelated. Estimates for σ^2_e and for σ^2_μ, needed to construct the transformed variables, are obtained respectively from the residual sum of squares of the within regression and from a regression on the groups' means (between estimator).

Interestingly the variance components estimator reduces to the OLS estimator when
$\theta = 0$, or equivalently, $\sigma^2_\mu = 0$, and to the within estimator when $\theta = 1$.

One disadvantage of the GLS variance components estimator is that it will be biased if the regressors are not independent of the μ_i. In applied economics correlation between the regressors and the individual effects can be expected to be quite common and as a result this presents a severe drawback for the GLS estimator. As noted above, whatever the correlation between the η_i and the regressors the within estimator will be unbiased and large *N* consistent. However, if the μ_i do satisfy the assumptions of the variance components model, the within estimator will not be as efficient as the GLS estimator. The within and the GLS estimators therefore imply different assumptions concerning the independence of the regressors and the individual effects. These assumptions can be tested by Hausman type tests of the significance of the difference between the estimators (Hausman and Taylor, 1981).

3.3 Empirical results

In this section we present the results obtained with the different estimation methods described above. We started by estimating a simpler version of the model that did not include any aggregate variables, i.e. we estimated the following model:

$$\ln H_{it} = \ln A_i + \alpha \ln V_{it} + (1-\alpha) \ln U_{it} + e_{it} \tag{16}$$

The results obtained are presented in the first three columns of Table 1. Note that to impose the homogeneity restriction of the coefficients in (16) the equation that was estimated was the following:

$$\ln \frac{H_{it}}{U_{it}} = \ln A_i + \alpha \ln \frac{V_{it}}{U_{it}} + e_{it}. \tag{17}$$

Table 1

	Eq.1			Eq.2		
	OLS	**WITHIN**	**GLS**	**OLS**	**WITHIN**	**GLS**
const	-1.81 (-10.26)	-	-2.45 (5.06)	-1.88 (-5.83)	-	-2.85 (-5.25)
α	0.344 (9.91)	0.0938 (2.04)	0.203 (5.06)	0.364 (10.36)	0.091 (1.87)	0.211 (5.01)
time dummies	no	no	no	yes	yes	yes
s.e.r.	1.688	1.517	1.603	1.634	1.459	1.542

As explained above the test between the OLS and the within specifications consists simply on testing for the equality of the η_i. The F statistic obtained $F_{(35,395)} = 3.9182$ clearly leads us to conclude that the intercepts for the 36 professions considered are not the same. Moreover the Hausman test of fixed versus random effects gives a χ^2 statistic with one degree of freedom of 24.6 validating therefore the within or fixed effects model.

In the next three columns of Table 1 we present the results obtained when the same equation was estimated introducing time dummies. Comparing the standard errors of the regressions one can see that the global fit of the equations improved, as the set of time dummies is significant for all three models. Notice that the values obtained for α do not change much for the same specification with or without time dummies. Again the F test for the equality of the intercepts $F_{(35,384)} = 4.06$ validates the within model against the OLS regression, implying that matching efficiency varies across professions. Moreover the Hausman test gives a χ^2 with 12 degrees of freedom of 24.6, validating again the within or fixed effects model versus the GLS specification.

Inspection of the values taken by the time dummies with our preferred specification (the within model) tells us that hiring efficiency was specially above average for the years 1990 and 1995 and below in 1985 and 1986. These results however informative on the past performance of hirings do not directly relate the evolution of aggregate matching efficiency with the business cycle or with labour market institutional features, which seems much more important if one is not only interested in explaining past performances but also trying to understand the underlying operating mechanisms. We move therefore to the presentation of the results obtained when instead of time dummies we consider as explanatory variables aggregate indicators that vary over time.

The results obtained are presented in Table 2. Note that we only present the results obtained with the within model as in every case the F statistic for the equality of the intercepts and the Hausman test of the within versus the GLS specification clearly validated the within model.

Table 2

Dep Variable Hi/Ui	(i)	(ii)	(iii)	(iv)
Vi/Ui	0.1091	0.1136	0.1142	0.0986
	(2.27)	(2.40)	(2.41)	(2.12)
BC	3.336	3.054	1.742	4.173
	(1.52)	(1.43)	(0.87)	(2.08)
FPR	12.90	10.63	-4.316	-
	(1.30)	(1.54)	(0.87)	
WR	-3.417	-3.807	-	-0.425
	(-0.91)	(-1.40)		(-0.26)
rmin	-16.25	-14.42	-9.585	-8.197
	(-2.06)	(-2.55)	(-4.12)	(-2.09)
D85-89	-0.120	-	-	-
	(-0.30)			
D90-95	-0.422	-	-	-
	(-0.77)			
s.e.r.	1.482	1.480	1.483	1.482

In column (i) we present the results obtained with our initial specification.[1] Note that the estimated value for α is quite similar across the four equations presented in Table 2 and is also similar to the values obtained in Table 1 for the within model. This fact is reassuring as it suggests that the α parameter is quite robustly estimated. Also the aggregate variables considered show, in equation (i), the expected sign. Indeed a higher value for BC, which implies an expansionary period in the business cycle improves aggregate matching efficiency as expected. Similarly, the higher the average wage or the importance of the minimum wage the lower is aggregate matching efficiency. Note that aggregate matching efficiency seems more affected by the importance of the minimum wage than by the evolution of the real wage. This fact suggests that changes in the dispersion of wages or in the shape of the wage distribution across workers affect more matching efficiency than changes in its mean.

Also we obtain that, the higher the female participation rate, the better is aggregate matching efficiency. As in Portugal female participation rates, although showing a trend increase, seem to vary with the business cycle, as some discouraged female workers tend to simply leave the labour force when they become unemployed, we feel that this finding may simply reflect this phenomenon i.e. we fear that this variable may just be picking the business cycle. Moreover, we have also some concerns in terms of the possible endogeneity of this variable.

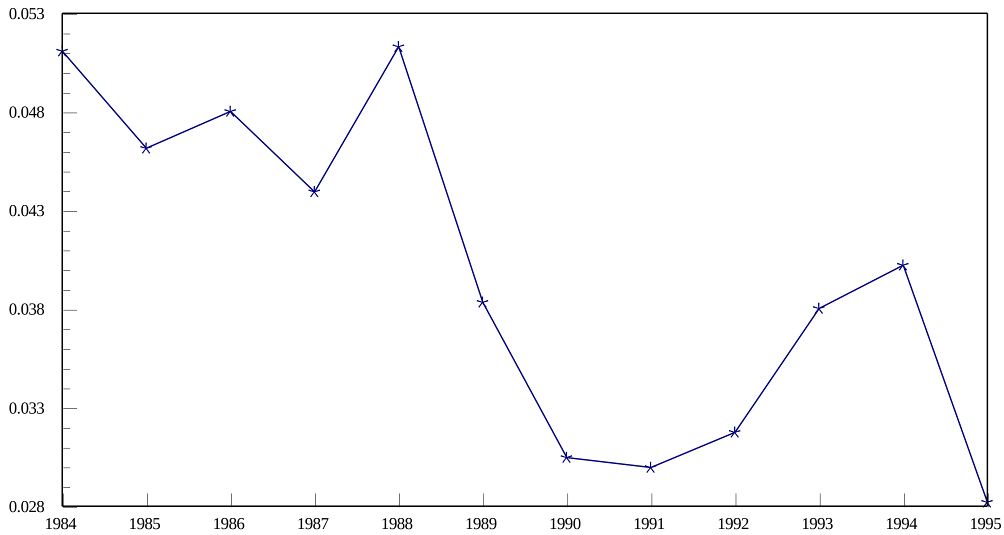
As explained above we considered two time dummy variables to try to isolate the effects of labour market legislation in terms of protection of the unemployed on matching efficiency. However, although these two variables show the expected sign and magnitudes in equation (i) they are not significantly estimated. We decided therefore to exclude them and obtained the results presented in column (ii). In this equation the estimated values of the parameters do not change much and the fit of the equation does not deteriorate significantly. We decided however to do some more experiments and in column (iii) we present the results obtained when we exclude the average real wage from the set of the regressors. The results obtained are not very satisfactory. The business cycle indicator and the female participation rate are no longer

[1] Note that we did not considered as an explanatory variable the male participation rate as the female participation rate showed always a better performance.

significative. This fact seems to suggest the existence of multicolinearity between these variables. Therefore, in the light of these results and of the considerations made above, we decided to exclude the participation rate from the set of explanatory variables and obtained the results presented in column (iv).

Fig. 1

The evolution of MMI



With this specification all the variables show the correct sign and, except for the average real wage, are significantly estimated. We decided however to keep the average real wage as an explanatory variable as we feel that the two wage variables make more sense together.

4. Measuring mismatch

In this section we construct the two mismatch indicators discussed before. The first one measures mismatch due to heterogeneity across professional labour markets and is simply obtained using the estimated value for α and the unemployment and vacancies data for the 36 professional groups considered. We will call this indicator MMI. Remember that MMI is given by (11) i.e.:

$$MMI = -\frac{1}{1-\alpha} \log\left[\sum f_i \left(\frac{v_i}{v}\right)^{\alpha} \left(\frac{u_i}{u}\right)^{1-\alpha}\right] \tag{18}$$

that can also be written as:

$$MMI = -\frac{1}{1-\alpha} \log\left[\sum \left(\frac{V_i}{V}\right)^{\alpha} \left(\frac{U_i}{U}\right)^{1-\alpha}\right]. \tag{19}$$

The obtained series for this indicator, using the estimated value for α from equation 4 (i.e. α = 0.098563) is presented in Figure 1.[2] Mismatch due to heterogeneity was higher in the first years

[2] Note that, had we considered instead the estimated value for a from equation (2) the obtained series would be almost identical.

of our sample, reaching its peak in 1988, and then declined until 1991, starting to increase again afterwards until 1994, dropping suddenly in 1995 reaching its minimum value.

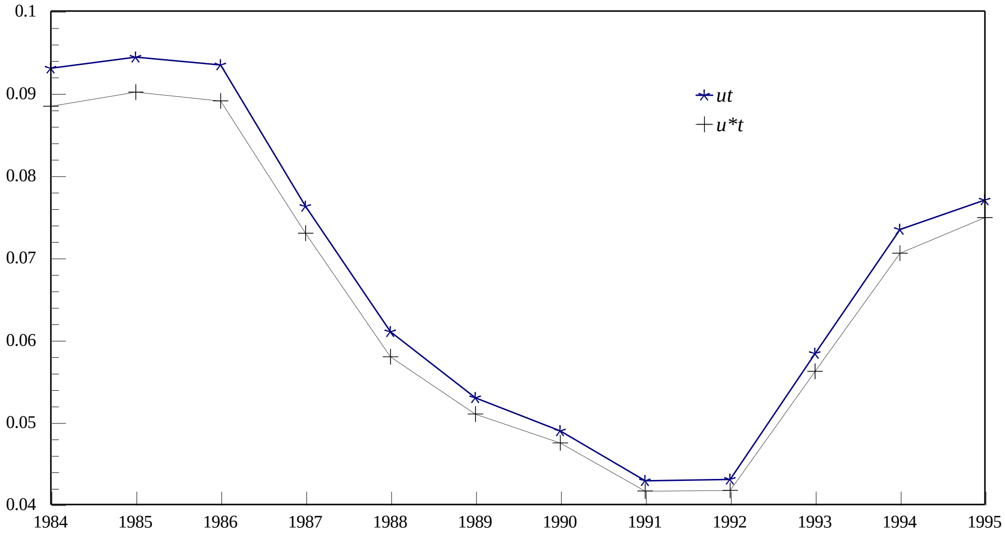
Having constructed this indicator we can now, using again equation (11), obtain the minimum aggregate unemployment rate compatible with the observed level of vacancies in each year, i.e.:

$$\log u_t^* = \log u_t - MMI_t. \tag{20}$$

The obtained series is represented with the actual unemployment rate in Figure 2.[3] Note that the two series follow each other quite closely, meaning that mismatch due to heterogeneity did never surmounted cyclical and or trend movements in the unemployment rate. Indeed this type of mismatch, although present, never represented an important source of unemployment, as it only accounted for a maximum of 0.46 percentage points in the unemployment rate.

Fig. 2

The minimum aggregate unemployment rate (u*t) and the actual unemployment rate



The other mismatch indicator, also discussed above, is the aggregate matching efficiency, $m(X_t)$, that fluctuates with the business cycle and labour market conditions. Recall that we assumed that matching efficiency could vary across professions and time in the following way

$$\log A_{it} = \log A_i + \log m(X_t) \tag{21}$$

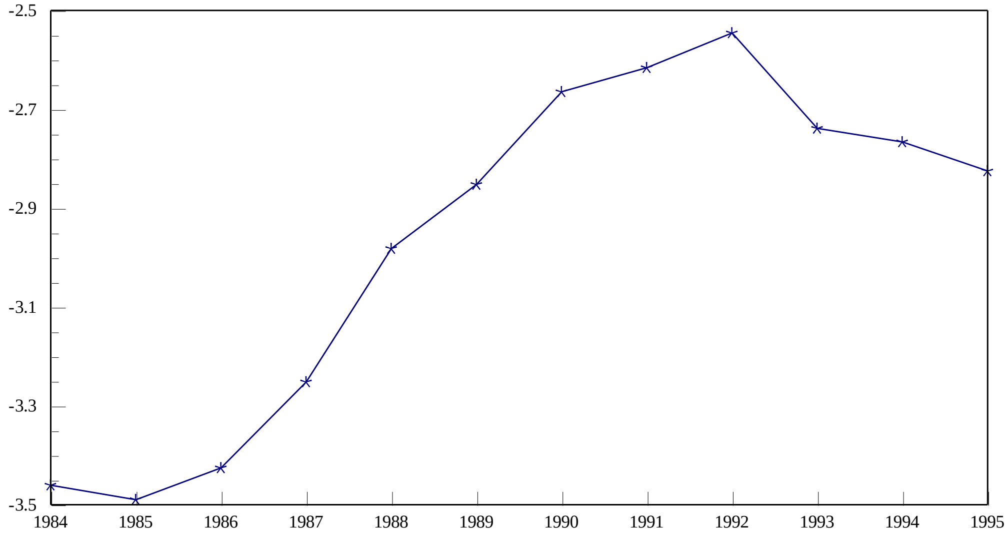
and that according to our preferred specification we have that:

$$\log m(X_t) = b_1 * wr + b_2 * rs\min_t + b_3 * BC_t. \tag{22}$$

[3] Note that what we call unemployment rate throughout all this work does not correspond to the usual definition of this term. Indeed we defined here u as the ratio between unemployment and employment whereas, usually the unemployment rate (ur) is defined as the ratio between unemployment and the labour force. This means that the relation between these two rates is the following: $u = ur/(1-ur)$.

Fig. 3

The evolution of aggregate matching efficiency



The series *log* $m(X_t)$, also obtained using the estimated values of the parameters from equation (4), is presented in Figure 3. We can see that aggregate matching efficiency in Portugal was lowest in the beginning of our sample and then increased steadily until 1992, starting to decline again afterwards. However, in 1995 aggregate matching efficiency was still above its mean sample level, in contrast to this year position in terms of the business cycle. See Figure 4. Indeed comparing Figures 3 and 4 one can see that aggregate matching efficiency followed the business cycle, mainly in its expansionary phase, showing nevertheless a certain lag, but that in the last three years of our sample the observed deterioration in matching efficiency was not as big as the contraction registered in activity. This suggests that the evolution in the wage variables eased somehow the tensions in the labour market. Note also that although the years 1994 and 1995 are below the GDP trend, the Portuguese economy showed signs of recovery already in 1994 when GDP stagnated and in 1995 with a GDP growth rate of 2.3 per cent.

5. The Beveridge Curve

Our theoretical model predicts the following relation between the minimum aggregate unemployment rate and the vacancy rate (see equation (10)):

$$\log u^* = cte - \frac{\alpha}{1-\alpha}\log v - \frac{1}{1-\alpha}\log m(X) \qquad (23)$$

that using our estimated values becomes:

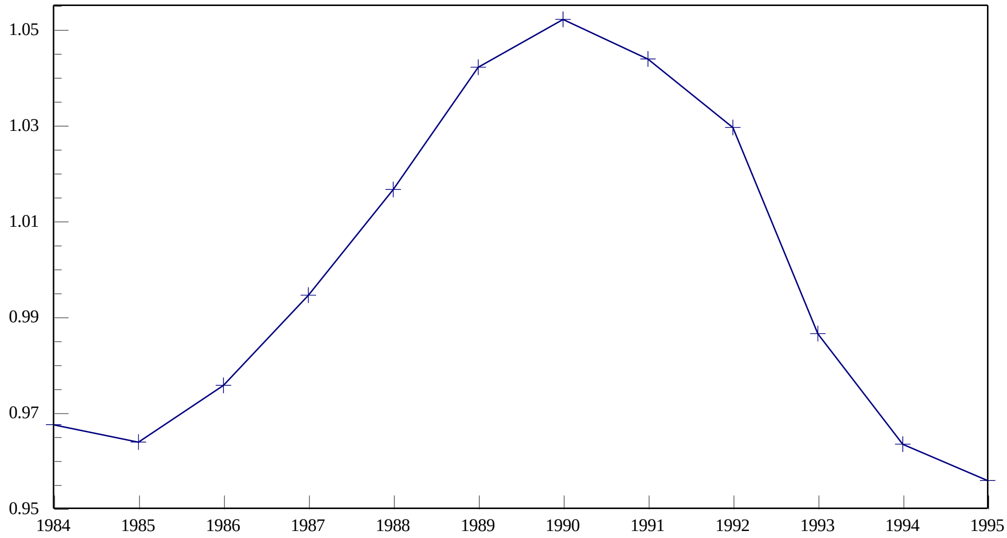
$$\log u^* = cte - 0.10934 \log v - 1.10934 \log m(X) \qquad (24)$$

To test whether indeed (24) fits our aggregate data we decided to estimate it using our constructed (estimated) series for u_t^* and *log* $m(X_t)$ i.e. we run the following regression from 1984 to 1995:

$$\log \hat{u}_t^* = a_1 + a_2 \log v_t + a_3 \log \hat{m}(X_t) \qquad (25)$$

Fig. 4

The business cycle



The results obtained using OLS and AR1 are as follows:

Table 3

T=12	**a1**	**a2**	**a3**
OLS	-5.88	-0.142	-0.725
	(-5.78)	(-1.02)	(-5.69)
	adj R^2 = 0.740	s.e.r.= 0.147	DW = 0.50
AR1	-5.60	-0.042	-0.875
	(-5.43)	(-0.34)	(-4.31)
	adj R^2 = 0.881	s.e.r.=0.107	DW = 1.18

The global fit is satisfactory and one can see that the coefficients show the right sign. Moreover the null hypothesis :

$$H_0 : a_3 = 1.10934$$

can not be rejected in the AR1 case. Also the null hypothesis:

$$H_0 : a_2 = 0.10934$$

is accepted both for AR1 and OLS, although in both cases the coefficient is not significantly estimated.

However, in the previous estimations we did not impose the restriction that the theoretical model predicts between a_2 and a_3. In order to do so we run the following regression:

$$\log \hat{u}_t^* - \log v_t = a_1 + a_3 \left(\log v_t + \log \hat{m}(X_t)\right) \tag{26}$$

The results obtained are presented below:

Table 4

	a1	**a3**
OLS	-4.91 (-4.55)	-0.915 (-8.25)
adj R^2 = 0.860	s.e.r.= 0.173	DW = 0.31
AR1	-5.73 (-5.76)	-1.00 (-10.16)
adj R^2 = 0.949	s.e.r.= 0.110	DW = 1.32

The restriction imposed is accepted in the AR1 case. Moreover, again the coefficients show the expected signs and are now significantly estimated in both cases. Also the null hypothesis:

$$H_0 : a_3 = 1.10934$$

can not be rejected in both cases. It seems therefore that our model, that was estimated using panel data, receives full support when tested with aggregate data.

We can therefore conclude that at the aggregate level the Beveridge curve is given by the following expression:

$$\log u_t = cte - 0.10934 \log v_t - 1.10934 \log m(X_t) + MMI_t \qquad (27)$$

However, in order to use (27) we have to estimate the constant term. To obtain it we simply run the following regression:

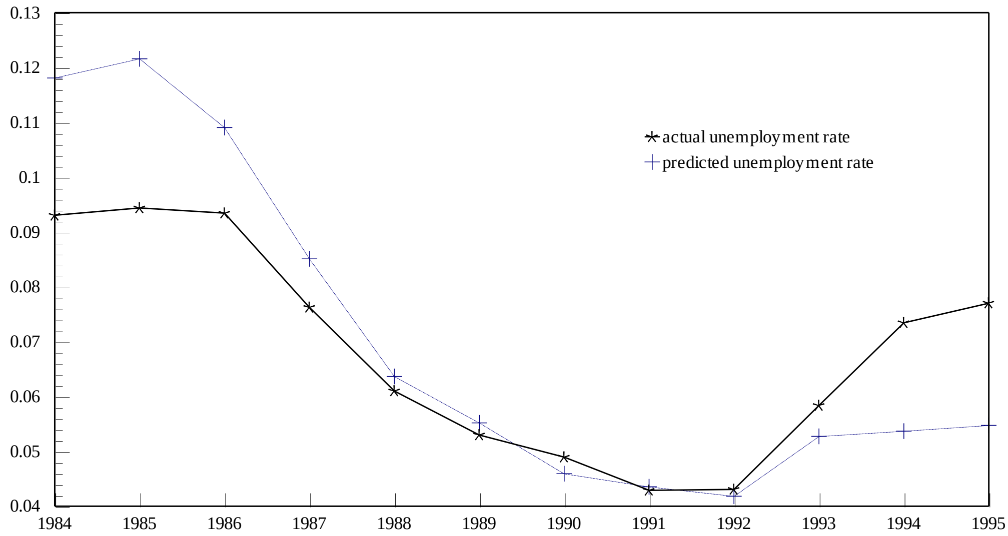
$$\log \hat{u}_t^* + 0.10934 \log v_t + 1.10934 \log \hat{m}(X_t) = cte + e_t \qquad (28)$$

obtaining a value of *-6.8*.

We can now, using the RHS of (27), obtain the unemployment rate predicted by the model and contrast it with the actual unemployment rate. The two series are presented in Figure 5. One can see that the constructed unemployment rate follows quite well the evolution of the observed rate. Nevertheless the model overpredicts unemployment in the first years of the sample while the opposite happens in the last two years. Therefore it seems that the model fits better the data in the expansionary phases of the business cycle than in contractionary phases, although being able to predict the turning points.

Fig. 5

Actual and predicted unemployment rate



In what concerns the behaviour of the model in the last two years considered, 1994 and 1995, the main reason for the obtained results lies in the evolution of the two matching indicators constructed. Indeed, according to MMI, matching inefficiency due to heterogeneity in labour markets improved in the end of the sample, while our aggregate matching efficiency indicator despite registering a deterioration in the last three years of the sample, seems to underpredict the observed contraction in the economy. Nevertheless, the observed unemployment rate in 1994 and 1995, deteriorated less than one would have expected just looking at the business cycle variable. (See Figure 4). These findings seem to suggest that the improvement obtained in matching efficiency during the last expansionary phase had some lasting effects, i.e. that the labour market in Portugal reacts now better to a contraction in activity then what used to be case in the mid-eighties. According to our results this fact is probably explained by the behaviour of wages and by an improvement in sector heterogeneity. A deeper investigation of these issues, clearly beyond the scope of this paper and it would certainly need more observations, is however required before we can make such a statement with full confidence.

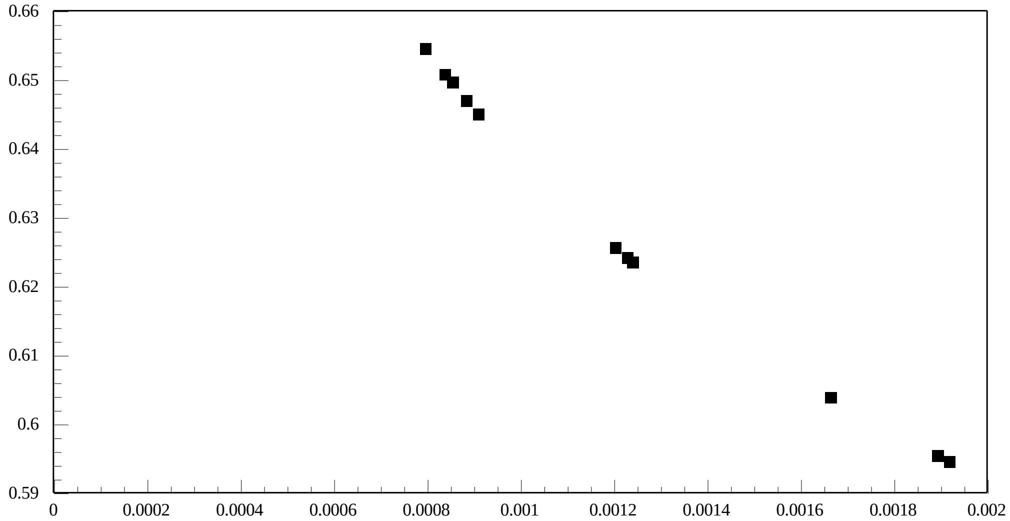
6. The structural unemployment rate

While expression (27) gives us the aggregate short run Beveridge curve that, as we have seen, is quite successful in explaining the behaviour of the aggregate unemployment rate, one is also interested in determining the long run position of this curve and in obtaining the trend unemployment rate.

Using our model and our estimation results it is quite easy to obtain estimates for these concepts. Indeed *the long run Beveridge curve*, emerges naturally in our framework, as the relation between unemployment and vacancy rates that would have been observed in a normal year in terms of aggregate matching efficiency (i.e. mainly in terms of the business cycle), in the absence of matching problems due to heterogeneity across professional labour markets.

Fig. 6

The long run Beveridge curve



Given our previous results it seems therefore natural to express the long run Beveridge curve in the following way:

$$\log u^* = -6.8 - 0.10934 \log v - 1.10934\, \overline{\log m(X_t)} \tag{29}$$

that we can rewrite as:

$$\log u^* = -9.76896 - 0.10934 \log v \tag{30}$$

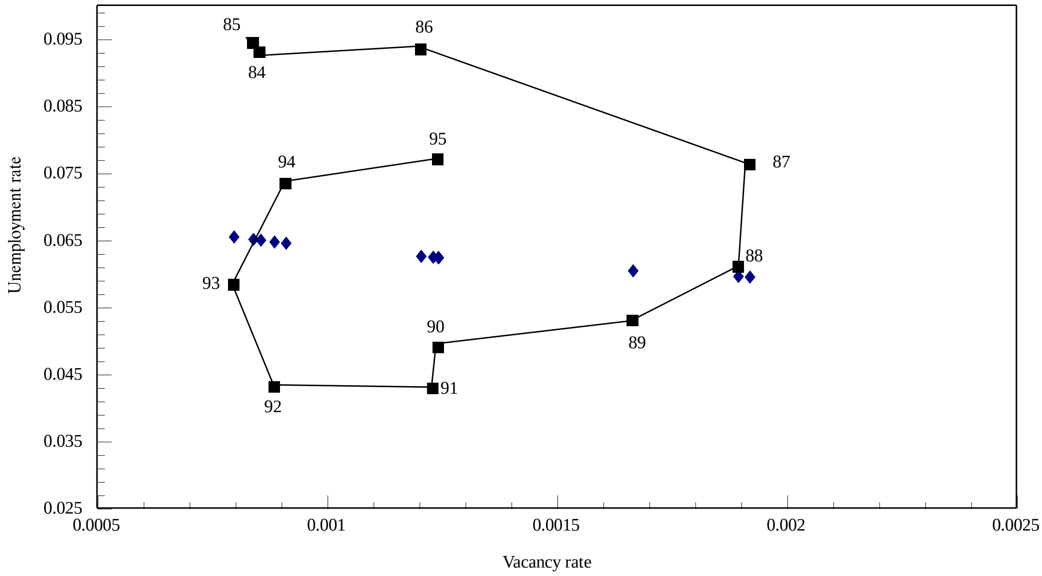
where we have proxied the long run level of the log of aggregate efficiency by its sample mean and set MMI to zero.

This long run Beveridge curve is plotted in Figure 6. It gives us for each year's observed vacancy rate what we will call the *structural or trend unemployment rate*, i.e. the minimum aggregate unemployment rate compatible with the observed vacancy rate had the year been normal in terms of the business cycle.

It is also of interest to compare each year's observed unemployment rate with its corresponding trend unemployment rate. In Figure 7 we have plotted the long run Beveridge curve together with the observed unemployment/vacancy rates pairs. One can see that for the years where GDP was above trend the Beveridge relation is shifted downwards, i.e. the same level of vacancies results in a smaller unemployment, while the opposite happens when the economy is in a recession. Interestingly in 1988 the Portuguese economy was on the long run Beveridge curve, i.e. observed unemployment and trend unemployment coincided in that year. Note also that in 1988 GDP was also identical to its trend value.

Fig. 7

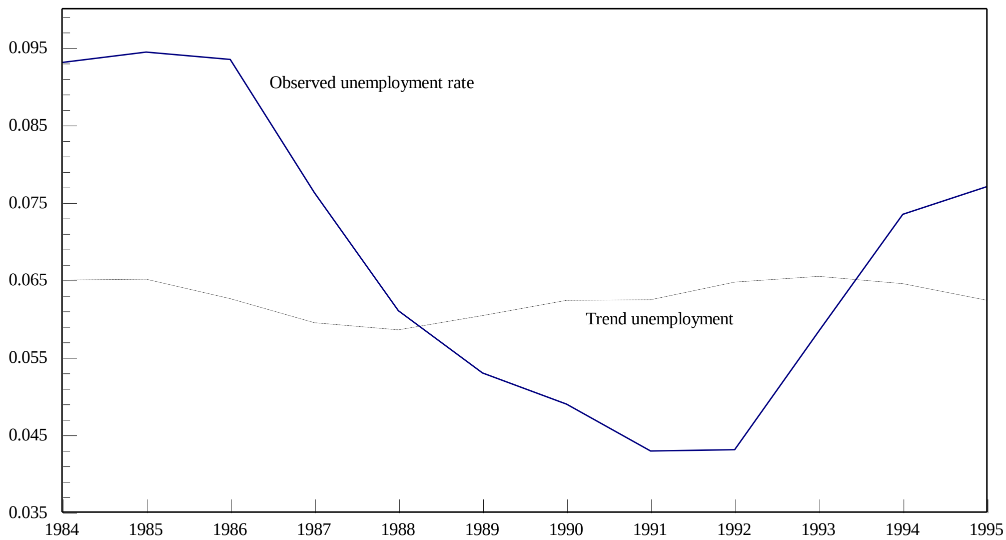
Structural unemployment and the observed unemployment/vacancy rates pairs



Moreover, a closer inspection of Figure 7 provides us with some insights on the evolution of the Portuguese labour market. First of all trend unemployment did not rise during the last decade in Portugal. See also Figure 8. This fact is mainly explained, in our framework, by the observed behaviour of the vacancy rate, that did not show any significative trend. See Figure 9. Indeed vacancies showed also a marked cyclical pattern following as well the business cycle, i.e. the vacancy rate increased when the economy started to recover and decreased when jobs were being filled as the economy expanded.

Fig. 8

Actual and trend unemployement

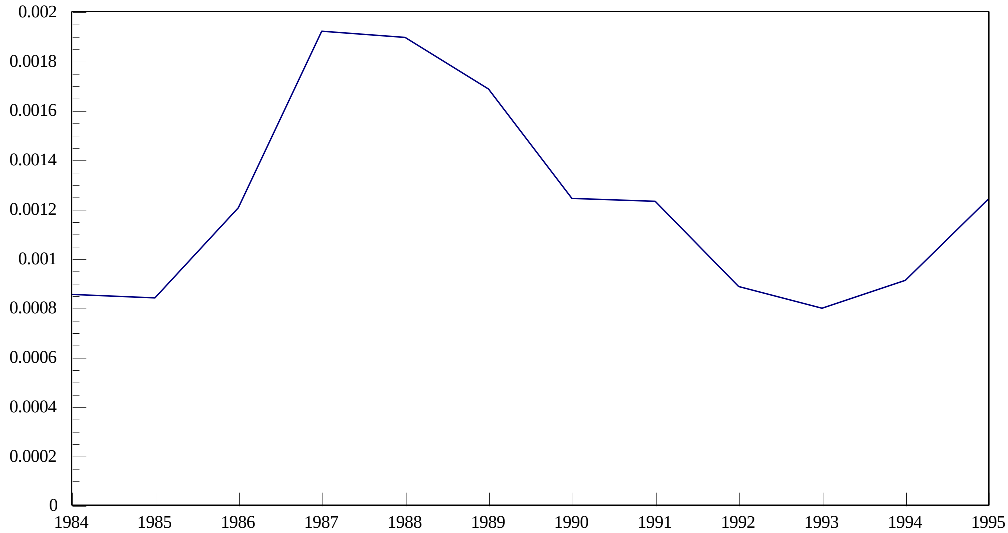


Also the observed behaviour of the unemployment/ vacancy pairs does not suggest any structural change in the Beveridge relationship i.e there is no strong evidence of a deterioration or improvement of the long run position of the Beveridge curve. Indeed the observed evolution seems to suggests that the observed shifts are perfectly explained by the cyclical behaviour of the Portuguese economy. After the 1984/85 recession that was characterised by a high level of unemployment and a small vacancy rate, vacancies started to increase and this movement was followed by a sharp reduction in unemployment as the economy expanded. The peak years of the Portuguese business cycle were characterised by low unemployment and a decreasing vacancy rate as jobs were being taken. The new recession implied again an increase in unemployment and, in the last years the vacancy rate started increasing again, suggesting recovery picking up.

Note however, that, as emphasised before, the last recession was characterised by low levels of unemployment for the same observed vacancies. So, this might suggest either a structural change in matching efficiency, i.e a change in the $m(X_t)$ function, or even a structural change in the long run Beveridge curve, i.e, a change in the a parameter. However, it is too soon to be able to discriminate between the hypothesis at stake, as we would need certainly more data points to test between the three competing hypothesis: no structural change, a structural change in aggregate matching efficiency or a change in the slope of the Beveridge curve. Nevertheless, note that when we estimated the hiring function using panel data, and time dummies instead of aggregate indicators, 1995 emerged as one of the years where matching efficiency was higher.

Fig. 9

The vacancy rate



7. Concluding Remarks

In this work we estimated a hiring function for the Portuguese economy using a panel of 36 professions for the years' 1984-95. We allowed matching efficiency to vary across professions and in time, being able to construct two mismatch indicators. The first measures mismatch due to heterogeneity across professional labour markets. The other relates aggregate matching efficiency to institutional changes in the labour market, wage behaviour and the business cycle. We conclude that mismatch due to heterogeneity, although present, did not explain much of the observed unemployment rate. On the contrary, changes in aggregate matching efficiency were quite successful in explaining Portuguese labour market performance.

We found evidence of a stable long run Beveridge relation [4] that is shifted in the short run by business cycle conditions. Moreover, we measured trend unemployment in Portugal and found that it did not increase during the last decade. Therefore, we can conclude that unemployment in Portugal seems to be mainly a cyclical phenomenon, and that recent changes in unemployment benefits do not seem to have worsen matching efficiency nor the Beveridge

[4] See also Luz and Pinheiro (1994) for the same result.

relation. Quite on the contrary, there is some evidence that seems to suggest an improvement in these fronts. It is however too soon to claim that this has happened.

References

Blanchard, O. and F. Jimeno, (1995), "Structural Unemployment: Spain vs. Portugal", *American Economic Review*, 85, 212-218.

Blanchard, O and P. Diamond, (1989), "The Beveridge Curve", *Brookings Papers on Economic Activity*, 1, 57-109.

Elmeskov, J., and M. MacFarlan, (1993), "Unemployment Persistence", *OECD Economic Studies*, 21, 59-88.

Entorf, H., (1995), "Matching Functions and Mismatch Trends: Evidence Based on Panel Data," University of Mannheim, mimeo.

Hausman, J. and W. E. Taylor, (1991), "Panel Data and Unobservable Individual Effects", *Econometrica*, 49,1377-1398.

Layard, R., S. Nickell and R. Jackman, (1991), *Unemployment: Macroeconomic Performance and the Labour Market*, Oxford University Press.

Luz, S. and M. Pinheiro, (1994), Wage rigidity and Job Mismatch in Europe: Some evidence", Working Paper 2-94, Banco de Portugal.