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Unemployment forecasts, time varying coefficient models and the Okun's law in Spanish regions

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Abstract

During the Great Recession, output and unemployment responses have differed markedly across Spanish regions. Our objective is to evaluate the relative accuracy of forecasting models based on the Okun's law compared to alternative approaches. In particular, we want to analyse if a time varying coefficient specification of the Okun's law provide better forecasts than alternative models in two different periods: a first period from 2002 to 2007 characterized by sustained economic growth in all provinces, and a second period from 2008 to 2013 characterized by the impact of the Great Recession. The obtained results allow us to conclude that, in general, the use of these models improve the forecasting capacity in most regions, but do not provide reliable forecast.

Keywords: unemployment forecasts, Okun's law, time-varying coefficient models, regional labor markets

JEL Classification Codes: C53, R23, J64

1. Introduction

During the last decades, the Spanish labour market has been characterised by high unemployment rates, particularly when compared to other European Union countries. Moreover, the low interregional geographical mobility together with the peculiarities of the collective bargaining systems until the last reforms have amplified the differences in unemployment rates from a regional perspective (López Bazo *et al.*, 2005).

More recently, the financial crisis, the burst of the housing bubble and the dramatic fall of employment in the construction sector during the Great Recession has magnified the problem. Given its social and political significance, forecasting unemployment rates is particularly important to help policy makers in their decision-making. As a result, the literature dealing with unemployment rate forecasting is consequently large: see, for instance, Funke (1992),

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Rothman (1998), Elliot and Timmerman (2008) or, more recently, Franses *et al*. (2014). The literature has also recently rediscovered (see Knoteck, 2007; Ball *et al.*, 2015 or Guisinger and Sinclair, 2015) the possibility of using the Okun's law as a simple but potentially powerful forecasting model. Using 1950's data for the US economy, Okun (1962) found an empirical negative relationship between changes in the unemployment rate and output growth. This relationship has been estimated and tested for several countries (see for instance Huang and Yen, 2013), but also for regions: Freeman (2000) and Pereira (2014) for the United States, Adanu (2005) for Canadian regions; Durech *et al*. (2014) for regions in the Czech Republic and Slovakia; Kangarsharju *et al*. (2012) for the Finnish regions; Christopoulos (2004), Karfakis *et al.* (2014), and Apergis and Rezitis (2014) for Greek regions; Marie-Estelle and Facchini (2013) for French regions and, for the Spanish regions, it is worth mentioning the research by Villaverde and Maza (2007 and 2009), Ballesteros *et al*. (2012), Martín-Román and Sylvina-Porras (2012). However, none of these studies are focused on regional forecasting but on the explanatory capacity of models based on the Okun's law.

The objective of this paper is to evaluate the relative accuracy of forecasting models based on the Okun's law compared to alternative approaches in the particular context of Spanish regions. We want to analyse if the use of time varying coefficient models improves the forecasting accuracy of the Okun's law when compared to fixed coefficient models in two different periods: a first period from 2002 to 2007 characterized by sustained economic growth in all provinces, and a second period from 2008 to 2013 characterized by the impact of the Great Recession. The use of time varying coefficient models in the context of unemployment forecasting has been scarce and, to our knowledge, inexistent at the regional level. In particular, Franses *et al*. (2004) consider time series univariate models with time-variation in the AR parameters and apply them to obtain unemployment forecasts for the US, Canada and Germany. Their results show that this model outperforms alternative models in terms of forecasting accuracy.

2. Methods

The Okun's law is given by the following expression:

$$\Delta UR_t = \alpha + \beta \cdot \Delta GDP_t + \varepsilon_t , \quad (1)$$

where ΔUR_t and ΔGDP_t denote, respectively, changes in the unemployment rate from *t-1* to *t* (or differences in logs) and output growth (usually measured by changes from *t-1* to *t* in the logarithm of Gross Domestic Product - GDP); α is an intercept; β, usually known as Okun's coefficient, explains how changes in the logarithm of output affect variations in the unemployment rate; and, ε_t denotes a random term. The ratio $-\frac{\alpha}{\beta}$ provides an estimate of the required output growth to stabilize the unemployment rate. The basic specification shown in Eq. (1) can also be augmented by the inclusion of lags of output and unemployment in order to take into account the possibility that the relationship between the two variables could not only be contemporaneous but a dynamic one.

An alternative version of the Okun's law relates the unemployment rate to the output gap (i.e., the difference between actual output and potential output - GDP_t^*). This alternative version of the law is given as follows:

$$UR_t = \alpha + \beta \cdot \left(GDP_t - GDP_t^*\right) + \varepsilon_t , \quad (2)$$

where the intercept α can be interpreted as the unemployment rate in the case of full employment. Eq. 2 can be reformulated as:

$$UR_t - UR_t^* = \beta \cdot \left(GDP_t - GDP_t^*\right) + \varepsilon_t , \tag{3}$$

where UR_t^* is the natural unemployment rate, and, so $UR_t - UR_t^*$ is the unemployment gap. Although probably the relationship captured by Eq. 3 is more meaningful than Eq. 1 from an economic point of view, the main problem is that potential output and the natural unemployment rate are not observable, so it is necessary to estimate them using filtering methods such as the Hodrick-Prescott or pass-band filters[1] before Eq. 3 can be empirically analysed. For this reason, and taking into account that the objective of this paper is to analyse Okun's law forecasting accuracy, we will use Eq. 1 instead of Eq. 3.

The strategy to test if the Okun's law can provide useful information to improve forecasts of regional unemployment rate in Spain has been the following. Four different sets of models have been considered (naïve, auto-regressive, fixed coefficient models and time varying coefficient models) to obtain forecasts for the unemployment rate of the different Spanish provinces and the Mean Absolute Percentual Error (MAPE) has been computed for different forecast horizons. The comparison of the MAPE values for the models not based in the Okun's law with those derived from it would permit to assess whether it is useful or not to improve unemployment forecasts.

Naïve methods

As usual in the literature, the naïve method considers that the value of the variable of interest in a particular period does not change from the last valid observation:

$$UR_t = UR_{t-1} . \tag{4}$$

A slightly different version of this approach assumes that changes in the variable are the same to the ones observed in the previous period:

$$UR_t = UR_{t-1} \cdot \Delta UR_{t-2} . \tag{5}$$

Autoregressive models

The widely known autoregressive model (also known as distributed-lags model) explains the behaviour of the endogenous variable as a linear combination of its own past values:

$$UR_t = \phi_1 UR_{t-1} + \phi_2 UR_{t-2} + ... + \phi_p UR_{t-p} + \varepsilon_t . \tag{6}$$

The key question is how to determine the number of lags that should be included in the model. We have considered different models with a minimum number of 1 lag up to a maximum of 3, selecting that model with the lowest value of the Akaike Information Criteria (AIC). In order to check the robustness of the results to different selection criteria, we have also considered the Schwartz criteria yielding exactly the same results.

Fixed and time varying coefficient models

Ordinary Least Squares (OLS) estimation of Eq. (1) allows to obtain forecasts for the unemployment rate. Eq. (1) can also be augmented with lags of GDP but also unemployment in order to take into account the dynamic response of unemployment to GDP shocks but also

[1] Moreover, there is no consensus in the literature on which of the different procedures is more appropriate to estimate the unobservable variables.

to control for the persistence of regional unemployment (hysteresis). In order to distinguish both sets of forecasts, we denote forecasts from Eq. (1) as "static Okun's law" while forecasts from the augmented Eq. (1) is denoted as "dynamic Okun's law".

However, as previously mentioned in the presence of structural instability, estimates of α and β will not be appropriate and lead to misleadings forecasts. For this reason, we also consider a time varying coefficient specification of the Okun's law. For simplicity, we only consider the time varying coefficient specification of the static version of the Okun's law. Time varying coefficient models try to consider in the specification and estimation of the model the instability in the relationship between the endogenous and the exogenous variables. This instability can be caused by structural changes but also by specification errors ((Dzciechciarz, 1989; Engle and Watson, 1987; Min and Zellner, 1993). Time varying coefficient models are usually formed by two equations: a first equation that captures the time evolution of the considered coefficients denoted by β_t:

$$\beta_t = \phi_t \cdot \beta_{t-1} + W_t \cdot \theta_t + \eta_t, \tag{7}$$

and where ϕ_t represents the magnitude of the change in the coefficient in each time period, W_t denotes potential explanatory variables of the value of β_t, θ_t are the coefficients associated to these variables and η_t is a random error term that is assumed to follow a normal distribution with zero mean and variance σ_η^2. The second equation is related to the equation of interest, in our case, the Okun's law, with Y_t denoting the endogenous variable, X_t the explanatory variables with time varying coefficients and Z_t other explanatory variables with non-time varying coefficients, denoted by γ:

$$Y_t = X_t \cdot \beta_t + Z_t \cdot \gamma + \varepsilon_t, \tag{8}$$

ε_t is a random error term following a normal distribution with zero mean and variance σ_ε^2.

Taking into account the previous literature and the arguments provided by Engle and Watson (1987) this general specification model is usually simplified for empirical work assuming that ϕ_t=1 and θ_t =0. This restricted specification is known as systematically varying coefficient models and, in this case, coefficients are assumed to behave as a random walk (Shively and Kohn, 1997). The system formed by the restricted specification of Eq. 6 and Eq. 7 can be transformed into a state-space model where the first is the state equation and the second is the measurement equation. In the particular case of the Okun's law the model to estimate would be the following one:

$$UR_t - UR_{t-1} = \alpha_t + \Delta GDP_t \cdot \beta_t + \varepsilon_t, \tag{9}$$

$$\alpha_t = \alpha_{t-1} + \eta_t, \tag{10}$$

$$\beta_t = \beta_{t-1} + \zeta_t. \tag{11}$$

The estimation of this model can be done using the Kalman filter, once the values of the hyperparameters of the model (variance of the random terms of the three equations) are estimated by maximum likelihood and the OLS estimates of the Okun's law are used as initial values.

3. Data

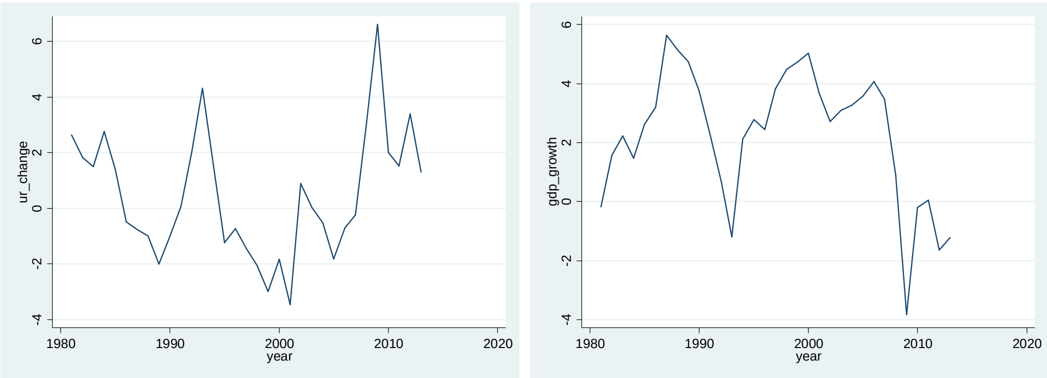
In order to carry out our analysis, we have used information for the 17 Spanish Autonomous Communities (NUTS-II level regions). Data for unemployment rates comes from the Spanish Labour Force Survey (LFS) provided by the National Institute of Statistics (INE) while data for real output growth comes from the Spanish Regional Accounts (SRA). Although unemployment rates data are available at the quarterly frequency, regional output is only available at the annual frequency. In both cases, data is available since 1980 up to 2013.

4. Results

Before moving to the analysis of the forecast competition, figure 1 shows the evolution of changes in unemployment and GDP growth for the Spanish economy for the considered period. As we can see from figure 1, it is not straightforward to conclude that the first difference of both series behave as stationary time series. This is a relevant point as this is a requirement of the Okun's law specification used to derive the different time series models used for the forecasting competition. Detailed results of the analysis of the time series properties of unemployment and GDP for Spain and the 17 Spanish Autonomous Communities using the Augmented Dickey Fuller test, Phillips and Perron test, Elliot-Rothenberg-Stock test, Schmidt-Phillips test, Kwiatkowski-Phillips-Schmidt-Shin test, Zivot-Andrews test and the Clemente-Montañes and Reyes test are available from the authors on request. Due to space limitations, we only show the results of the Augmented Dickey-Fuller test in table 1.

Results from table 1 permit us to conclude that, with the only exception of unemployment in the Basque country (País Vasco), in all Autonomous Communities at the usual significance levels we reject the null hypothesis that there is a unit root in the two variables after differentiating. Results from other unit roots or stationary tests are very similar and validate our empirical specification of the Okun's law. However, it is worth mentioning that, as it can be seen in the first panel of table 1, in a few regions like Asturias, Extremadura and La Rioja a different specification could perhaps be more appropriate. However, we prefer to keep a homogenous specification across the considered regions.

Figure 1. Changes in unemployment and GDP growth – Spain 1980- 2013



In order to evaluate the relative forecasting accuracy of the models, for each province all models were estimated for two different periods: until 2001 and until 2007. This allows us to consider two different periods to assess the capacity of the model in terms of forecasting: a first period from 2002 to 2007 and a second period from 2008 to 2013. The first corresponds to a period of sustained economic growth in all provinces, while the second one is clearly a recessionary period. For the two periods, models are reestimated in each year and forecasts are computed. Given the availability of actual values, forecast errors for each province and method can be computed in a recursive way (i.e., for the 1 year forecast horizon, 6 forecast errors can be computed for each province and period)[2]. In order to summarise this information, the Mean Absolute Percentage Error (MAPE) [3] has been computed. Its values provide useful information in order to analyse the forecast accuracy of each method, so methods can be ranked according to their values. For the 2 years forecast horizon, the strategy has been similar. The results of our forecasting competition are shown in tables 2 and 3. In particular, the average values of the MAPE obtained from recursive forecasts for 1 and 2 yearss ahead for the different models and provinces are shown in these tables. The obtained results permit to conclude that, as expected, forecasts errors increase in the second period when compared to the first one. Regarding the forecast accuracy of the different methods, in most cases the fixed and the time varying coefficient specifications of the Okun's law provide more accurate forecasts than the rest of the methods, being the autoregressive model the one usually displaying the highest MAPE values. However, it is worth mentioning that, for most regions, the accuracy of the models is limited as the MAPE is usually above the 5% threshold. For instance, the values of the MAPE are clearly above the average in the three regions where the ADF test yielded some doubts about the validity of the specification (Asturias, Extremadura and La Rioja), so it is possible that in some regions forecasting accuracy could be improved if we deviate for the common specification assumed in this paper.

However, one key question that should be addressed is whether the reduction in MAPE when comparing models based and not based in the Okun's law is statistically significant. With this aim, we have calculated the measure of predictive accuracy proposed by Diebold and Mariano (1995) between the two best models based and not based in the Okun's law for the two subperiods and two forecast horizon considered in our analysis. Given these two competing forecasts and the actual series for each quantitative variable, we have calculated the S(1) measure which compares the mean difference between a loss criteria (in this case, the root of the MAPE) for the two predictions using a long-run estimate of the variance of the difference series. In order to estimate this long run variance from its autocovariance function, we have used the Bartlett kernel, as it guarantees that variance estimates are positive definite, while the maximum lag order has been calculated using the Schwert criterion as a function of the sample size. The results are shown in tables 4 and 5. A negative value of the S(1) statistics indicates that the first method is better than the second while a positive value of S(1) indicates the opposite. As we can see from both tables, the comparison is nearly always carried out between naïve models and fixed coefficient specifications of the Okun's law (static or dynamic) in the first period and between naïve models and time-varying coefficient specifications of the Okun's law in the second period. In general, results do not support the view that forecast accuracy improve when Okun's law models are used. However, the power of the Diebold-Mariano test could be affected by the short number of forecasts that we are comparing. For this reason, the results of the pair-wise comparison of the considered forecasting methods using a panel version of the Diebold-Mariano test as in Bernoth and Pick (2011) are shown in table 6. In particular, the test statistic is calculated as follows:

$$\overline{S(1)} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} S_i(1). \qquad (12)$$

[2] As highlighted by the referee, ex-post forecasts are based on actual values of GDP that (although it is not a realistic assumption for real time forecasting) does not affect the validity of our comparison between fixed and time-varying coefficient models. In any case, we recognise that the values for the measures of forecasting accuracy that are calculated across the paper can be understood as lower bounds as the use of regional GDP forecasts will add higher uncertainty to the unemployment forecasts.

[3] $MAPE = \frac{1}{T} \sum_{t=1}^{T} \frac{|UR_t - \hat{U}R_t|}{UR_t} .100$, where $\hat{U}R_t$ is the forecast of the unemployment rate for period *t* from the different forecasting techniques. According to the MAPE's value, it is usual in the literature to establish that a value below 3% indicates an excellent performance, a value between 3% and 5% a good performance and a value above 5% a bad forecasting performance.

Table 1. Results of the Augmented Dickey-Fuller test

Level of the series is I(1)	Unemployment rate							Gross Domestic Product						
		Trend and intercept			Intercept		None		Trend and intercept			Intercept		None
Region	lag	test	trend	int	test	int	test	lag	test	trend	int	test	int	test
Spain	0	-2.762	2.646	3.961	-2.745	3.777	-2.761	0	-2.535	2.652	3.970	-2.068	2.145	-1.450
Andalucía	0	-2.825	2.715	4.072	-2.849	4.058	-2.844	0	-3.266	4.074	6.111	-2.662	3.544	-1.838
Aragón	0	-3.163	3.615	5.420	-3.053	4.664	-3.078	0	-4.154	6.353	9.525	-3.372	5.692	-2.129
Asturias, Principado de	0	-4.389	6.538	9.805	-4.451	9.910	-4.440	0	-4.255	6.180	9.237	-3.782	7.184	-2.964
Balears, Illes	0	-3.481	4.057	6.059	-3.467	6.039	-3.491	0	-4.282	6.213	9.251	-2.793	3.954	-1.942
Canarias	0	-3.530	4.310	6.465	-3.636	6.609	-3.647	0	-3.354	3.841	5.739	-3.225	5.223	-2.742
Cantabria	0	-3.312	3.747	5.601	-3.252	5.308	-3.247	0	-3.591	4.381	6.567	-3.360	5.649	-2.476
Castilla - La Mancha	3	-3.639	4.456	6.683	-3.434	5.898	-3.504	0	-2.757	3.025	4.537	-2.337	2.732	-1.606
Castilla y León	0	-2.946	3.004	4.477	-2.929	4.319	-2.962	0	-2.779	2.643	3.925	-2.572	3.347	-2.078
Cataluña	0	-3.097	3.226	4.838	-3.000	4.501	-2.893	0	-6.263	14.656	21.914	-5.039	12.749	-3.110
Comunitat Valenciana	0	-3.251	3.849	5.755	-3.233	5.243	-3.284	0	-3.597	4.754	7.114	-3.353	5.639	-2.441
Extremadura	0	-5.049	8.500	12.749	-5.121	13.112	-5.087	0	-4.741	7.832	11.743	-3.904	7.623	-2.841
Galicia	0	-3.204	3.451	5.175	-3.263	5.325	-3.157	0	-3.465	4.098	6.128	-3.506	6.165	-2.599
Madrid, Comunidad de	0	-3.076	3.217	4.823	-3.065	4.698	-3.108	0	-2.814	2.976	4.449	-2.358	2.795	-1.609
Murcia, Región de	0	-3.090	3.242	4.858	-3.077	4.740	-3.067	0	-2.879	2.930	4.376	-2.810	3.967	-2.150
Navarra, Comunidad Foral de	0	-3.048	3.209	4.812	-2.881	4.152	-2.914	0	-3.713	4.662	6.947	-3.692	6.862	-2.813
País Vasco	0	-3.315	3.869	5.775	-3.421	5.882	-3.486	0	-2.895	2.916	4.338	-2.938	4.354	-2.470
Rioja, La	4	-4.403	6.794	10.132	-4.236	9.030	-4.339	0	-4.986	8.340	12.471	-4.666	10.924	-3.466

Highlighted cells indicate a rejection of the null hypothesis at the 0.05 significance level.

Table 1. Results of the Augmented Dickey-Fuller test (cont.)

Series' first difference is I(1)	Unemployment rate							Gross Domestic Product						
		Trend and intercept			Intercept		None		Trend and intercept			Intercept		None
	lag	test	trend	int	test	int	test	lag	test	trend	int	test	int	test
Spain	2	-3.519	4.138	6.194	-2.080	2.219	0.117	0	-5.500	10.150	15.215	-1.661	19.200	-5.776
Andalucía	0	-6.364	13.573	20.359	-1.182	1.176	-6.584	0	-7.044	16.790	25.125	-1.742	15.574	-6.183
Aragón	0	-6.001	12.066	18.039	-0.950	0.721	-6.180	0	-7.180	17.790	26.519	-1.844	17.263	-6.753
Asturias, Principado de	1	-7.346	18.041	27.053	-1.739	1.685	0.376	1	-7.732	19.941	29.905	-1.887	4.260	2.109
Balears, Illes	0	-5.973	11.924	17.876	-1.196	1.119	-6.183	0	-7.373	18.123	27.182	-4.119	40.778	-6.856
Canarias	4	-4.697	7.356	11.033	-1.781	1.593	-0.081	1	-5.572	10.355	15.525	-1.380	2.267	1.574
Cantabria	0	-6.306	13.321	19.981	-1.032	1.214	-6.519	3	-4.688	7.335	11.002	-1.382	1.927	1.335
Castilla - La Mancha	3	-4.471	6.733	10.097	-1.952	1.907	-0.171	0	-5.731	10.950	16.424	-1.419	15.285	-6.045
Castilla y León	0	-5.686	10.815	16.211	-1.275	1.367	-5.834	4	-3.743	4.754	7.114	-1.595	2.124	1.229
Cataluña	1	-6.619	14.714	22.048	-1.849	1.956	0.459	0	-9.106	28.711	42.655	-1.451	10.835	-7.647
Comunitat Valenciana	1	-5.918	11.689	17.534	-2.065	2.139	-0.100	0	-7.529	19.072	28.597	-1.050	8.688	-6.890
Extremadura	0	-10.443	36.519	54.734	-1.680	1.803	-10.770	1	-7.150	17.117	25.661	-2.632	6.995	2.368
Galicia	0	-7.278	17.688	26.514	-2.416	4.575	-7.487	0	-7.488	18.694	28.039	-0.598	11.119	-7.551
Madrid, Comunidad de	0	-6.926	16.041	24.060	-1.040	0.635	-7.161	1	-5.585	10.416	15.612	-1.917	3.388	1.637
Murcia, Región de	2	-3.631	4.454	6.677	-2.315	2.724	0.025	0	-7.777	20.171	30.248	-0.945	11.685	-7.412
Navarra, Comunidad Foral de	2	-4.253	6.045	9.066	-1.334	0.906	-0.052	0	-9.479	30.048	45.031	-1.049	11.299	-8.506
País Vasco	2	-3.392	3.842	5.753	-1.631	1.336	-0.327	4	-4.151	5.781	8.637	-1.524	3.071	1.874
Rioja, La	4	-3.603	4.688	7.032	-2.502	3.152	-0.089	3	-4.702	7.394	11.063	-1.480	2.672	1.688

Highlighted cells indicate a rejection of the null hypothesis at the 0.05 significance level.

Table 2. 1 year ahead MAPE

	First period						Second period					
	Estimation 1980-2001 / *ex-post* forecast 2002-2007						Estimation 1980-2007 / *ex-post* forecast 2008-2013					
				Fixed coefficients		Okun -				Fixed coefficients		Okun -
1 year ahead MAPE	Naïve 1	Naïve 2	Autoregressive	Okun-Static	Okun-Dynamic	Variable	Naïve 1	Naïve 2	Autoregressive	Okun-Static	Okun-Dynamic	Variable
Spain	7.25	13.92	12.40	5.86	8.11	8.25	16.63	14.97	15.87	5.81	6.82	5.76
Andalucía	8.52	13.67	11.45	6.83	9.74	8.26	15.37	11.34	12.51	6.02	6.79	6.12
Aragón	9.39	20.25	17.85	18.74	20.52	20.68	19.62	15.76	18.21	7.18	9.74	6.15
Asturias, Principado de	10.79	26.35	20.03	7.83	17.69	14.50	15.32	13.43	14.93	8.03	6.87	5.59
Balears, Illes	16.38	19.67	11.52	12.59	12.54	10.24	16.87	15.08	16.18	11.36	12.42	10.21
Canarias	4.51	9.08	6.96	3.44	5.32	5.50	16.34	16.04	15.69	9.67	10.75	7.72
Cantabria	13.50	20.24	19.17	10.11	14.17	11.92	17.82	13.91	14.73	10.40	8.97	3.33
Castilla - La Mancha	6.84	11.70	10.20	4.54	9.93	9.82	19.25	18.84	19.81	14.79	16.30	12.93
Castilla y León	9.11	14.98	11.81	6.00	10.37	13.62	16.44	14.00	13.27	8.57	10.56	6.74
Cataluña	11.31	18.83	14.94	10.15	11.62	11.83	17.65	18.59	20.59	5.92	6.80	6.02
Comunitat Valenciana	8.37	13.56	10.75	7.78	8.87	8.70	16.35	16.62	17.75	6.70	7.67	7.40
Extremadura	10.78	25.18	12.29	10.32	12.08	11.46	14.37	14.09	13.91	16.63	16.55	10.22
Galicia	14.24	21.66	15.06	11.29	13.50	15.20	15.94	11.55	11.65	7.20	7.51	6.45
Madrid, Comunidad de	3.72	16.39	12.88	8.39	8.09	9.34	16.50	15.47	13.91	7.66	9.23	8.17
Murcia, Región de	8.65	18.20	11.69	10.72	11.26	11.90	18.67	14.69	15.37	10.86	11.20	10.85
Navarra, Comunidad Foral de	7.05	12.92	9.27	9.38	8.19	11.26	19.11	17.25	17.86	11.64	12.00	11.66
País Vasco	9.24	17.70	17.40	8.65	11.52	11.03	15.64	25.18	22.74	7.20	10.77	6.60
Rioja, La	11.92	30.81	13.72	12.21	20.00	13.48	18.65	17.51	16.93	17.44	17.24	16.55
Average	9.66	18.31	13.35	9.35	12.08	11.69	17.05	15.85	16.24	9.84	10.67	8.39
Standard deviation	3.18	5.46	3.50	3.40	4.01	3.24	1.53	3.12	2.90	3.48	3.29	3.17

Table 3. 2 years ahead MAPE

	First period Estimation 1980-2001 / *ex-post* forecast 2002-2007						Second period Estimation 1980-2007 / *ex-post* forecast 2008-2013					
				Fixed coefficients		Okun -				Fixed coefficients		Okun -
2 years ahead MAPE	Naïve 1	Naïve 2	Autoregressive	Okun-Static	Okun-Dynamic	Variable	Naïve 1	Naïve 2	Autoregressive	Okun-Static	Okun-Dynamic	Variable
Spain	15.76	16.99	14.74	8.68	11.11	11.71	30.34	14.71	18.51	9.42	11.57	9.35
Andalucía	18.66	16.04	16.98	14.53	15.73	12.50	27.59	12.32	16.14	8.58	10.78	7.17
Aragón	10.42	21.71	15.46	25.23	23.32	27.18	34.84	14.44	21.97	12.20	13.14	9.65
Asturias, Principado de	16.15	29.61	25.01	10.51	18.86	24.40	32.35	16.51	32.25	14.71	13.25	6.95
Balears, Illes	26.42	29.11	18.17	20.52	24.28	16.15	28.49	17.28	22.69	17.37	16.11	11.61
Canarias	6.61	9.03	9.00	5.42	7.59	8.88	27.23	16.80	21.32	13.85	13.10	9.53
Cantabria	29.69	29.66	34.07	23.20	22.65	14.10	33.56	15.80	25.84	19.82	14.50	2.88
Castilla - La Mancha	9.83	15.18	12.54	7.27	13.01	13.79	34.28	17.61	22.00	21.88	17.52	12.78
Castilla y León	17.65	17.55	13.49	12.73	16.09	20.10	29.58	14.32	18.66	13.10	14.25	7.80
Cataluña	24.87	22.18	14.55	19.72	19.85	18.29	32.77	18.73	21.56	8.77	11.07	7.88
Comunitat Valenciana	14.12	18.14	13.02	9.97	11.70	10.84	29.88	16.47	19.14	10.53	12.10	10.29
Extremadura	17.46	19.70	19.81	14.85	17.50	10.00	28.91	12.21	26.87	33.02	34.22	10.08
Galicia	28.82	29.20	28.87	22.28	22.87	23.91	31.55	12.67	22.36	13.35	12.80	7.18
Madrid, Comunidad de	6.54	14.35	13.80	14.46	12.93	20.46	29.54	14.93	21.31	12.43	15.50	12.16
Murcia, Región de	16.90	16.58	18.10	15.33	15.47	16.04	31.64	15.38	21.38	14.96	15.36	12.68
Navarra, Comunidad Foral de	9.45	11.85	10.97	17.51	12.76	18.18	33.91	18.21	23.15	19.39	14.75	14.01
País Vasco	17.62	18.22	13.88	7.35	11.74	10.52	29.66	22.71	24.82	6.60	9.52	4.98
Rioja, La	12.53	25.68	17.34	14.42	19.18	20.51	34.09	16.32	26.34	29.28	27.19	18.21
Average	16.69	20.22	17.36	15.02	16.80	16.81	31.17	16.04	22.81	15.87	15.60	9.76
Standard deviation	7.08	6.30	6.33	5.66	4.70	5.30	2.41	2.53	3.57	6.88	5.98	3.56

Table 4. Results of the Diebold-Mariano test for 1 year ahead forecasts

	First period				Second period			
	Estimation 1980-2001 / *ex-post* forecast 2002-2007				Estimation 1980-2007 / ex-post forecast 2008-2013			
1 year ahead	Best univariate model	Best Okun-based model	DM test S(1)	DM test p-value	Best univariate model	Best Okun-based model	DM test S(1)	DM test p-value
Spain	Naïve 1	Okun-Static	0.93	0.35	Naïve 2	Okun - Variable	2.31	0.02
Andalucía	Naïve 1	Okun-Static	0.91	0.36	Naïve 2	Okun-Static	0.19	0.85
Aragón	Naïve 1	Okun-Static	-2.97	0.00	Naïve 2	Okun - Variable	2.04	0.04
Asturias, Principado de	Naïve 1	Okun-Static	1.74	0.08	Naïve 2	Okun - Variable	1.92	0.06
Balears, Illes	Autoregressive	Okun - Variable	0.28	0.78	Naïve 2	Okun - Variable	0.35	0.73
Canarias	Naïve 1	Okun-Static	1.09	0.27	Autoregressive	Okun - Variable	1.90	0.06
Cantabria	Naïve 1	Okun-Static	2.40	0.02	Naïve 2	Okun - Variable	2.30	0.02
Castilla - La Mancha	Naïve 1	Okun-Static	1.87	0.06	Naïve 2	Okun - Variable	1.58	0.12
Castilla y León	Naïve 1	Okun-Static	1.32	0.19	Autoregressive	Okun - Variable	3.88	0.00
Cataluña	Naïve 1	Okun-Static	0.95	0.34	Naïve 1	Okun-Static	1.66	0.10
Comunitat Valenciana	Naïve 1	Okun-Static	0.36	0.72	Naïve 1	Okun-Static	1.55	0.12
Extremadura	Naïve 1	Okun-Static	0.53	0.60	Autoregressive	Okun - Variable	1.87	0.06
Galicia	Naïve 1	Okun-Static	1.32	0.19	Naïve 2	Okun - Variable	1.70	0.09
Madrid, Comunidad de	Naïve 1	Okun-Dynamic	-1.53	0.13	Autoregressive	Okun-Static	1.30	0.19
Murcia, Región de	Naïve 1	Okun-Static	-0.70	0.48	Naïve 2	Okun - Variable	1.05	0.29
Navarra, Comunidad Foral de	Naïve 1	Okun-Dynamic	-0.35	0.73	Naïve 2	Okun-Static	1.67	0.10
País Vasco	Naïve 1	Okun-Static	0.13	0.90	Naïve 1	Okun - Variable	1.73	0.08
Rioja, La	Naïve 1	Okun-Static	-0.33	0.74	Autoregressive	Okun - Variable	0.23	0.82

Null Hypothesis: Forecast accuracy is equal. Alternative Hypothesis: Forecast accuracy is different. A negative value of S(1) indicates that the first method is better than the second while a positive value of S(1) indicates the opposite. Highlighted cells indicate a rejection of the null hypothesis at the 0.05 significance level.

Table 5. Results of the Diebold-Mariano test for 2 years ahead forecasts

	First period				Second period			
	Estimation 1980-2001 / *ex-post* forecast 2002-2007				Estimation 1980-2007 / ex-post forecast 2008-2013			
			DM test				DM test	
2 years ahead	Best univariate model	Best Okun-based model	S(1)	p-value	Best univariate model	Best Okun-based model	S(1)	p-value
Spain	Autoregressive	Okun-Static	2.17	0.03	Naïve 2	Okun - Variable	0.79	0.43
Andalucía	Naïve 2	Okun - Variable	1.03	0.31	Naïve 2	Okun - Variable	1.64	0.10
Aragón	Naïve 1	Okun-Dynamic	-1.91	0.06	Naïve 2	Okun - Variable	0.65	0.51
Asturias, Principado de	Naïve 1	Okun-Static	1.82	0.07	Naïve 2	Okun - Variable	1.42	0.16
Balears, Illes	Autoregressive	Okun - Variable	0.35	0.73	Naïve 2	Okun - Variable	0.94	0.34
Canarias	Naïve 1	Okun-Static	1.73	0.08	Naïve 2	Okun - Variable	1.30	0.20
Cantabria	Naïve 2	Okun - Variable	3.48	0.00	Naïve 2	Okun - Variable	2.15	0.03
Castilla - La Mancha	Naïve 1	Okun-Static	1.68	0.09	Naïve 2	Okun - Variable	1.03	0.30
Castilla y León	Autoregressive	Okun-Static	0.19	0.85	Naïve 2	Okun - Variable	1.99	0.05
Cataluña	Autoregressive	Okun - Variable	-0.99	0.32	Naïve 2	Okun - Variable	1.30	0.19
Comunitat Valenciana	Autoregressive	Okun-Static	1.03	0.30	Naïve 2	Okun - Variable	1.01	0.31
Extremadura	Naïve 1	Okun - Variable	1.22	0.22	Naïve 2	Okun - Variable	0.62	0.54
Galicia	Naïve 1	Okun-Static	1.58	0.11	Naïve 2	Okun - Variable	0.98	0.00
Madrid, Comunidad de	Naïve 1	Okun-Dynamic	-2.01	0.04	Naïve 2	Okun - Variable	0.41	0.68
Murcia, Región de	Naïve 2	Okun-Static	0.40	0.69	Naïve 2	Okun - Variable	0.57	0.57
Navarra, Comunidad Foral de	Naïve 1	Okun-Dynamic	-0.64	0.52	Naïve 2	Okun - Variable	1.09	0.28
País Vasco	Autoregressive	Okun-Static	1.09	0.28	Naïve 2	Okun - Variable	2.51	0.01
Rioja, La	Naïve 1	Okun-Static	-0.68	0.50	Naïve 2	Okun - Variable	-0.39	0.69

Null Hypothesis: Forecast accuracy is equal. Alternative Hypothesis: Forecast accuracy is different. A negative value of S(1) indicates that the first method is better than the second while a positive value of S(1) indicates the opposite. Highlighted cells indicate a rejection of the null hypothesis at the 0.05 significance level.

Table 6. Results of the Panel Diebold-Mariano test

1 year ahead - 1st period	Naïve 1	Naïve 2	AR	Okun (fixed)		Okun (variable)
				Static	Dynamic	
Naïve 1 vs.		-5.70	-3.35	**1.75**	-2.45	-2.37
Naïve 2 vs.	5.70		7.66	**6.56**	7.31	5.39
AR vs.	3.35	-7.66		**4.40**	2.89	1.95
Okun (fixed) – static vs.	**-1.75**	**-6.56**	**-4.40**		**-3.79**	**-5.44**
Okun (fixed) – dynamic vs.	2.45	-7.31	-2.89	**3.79**		-0.45
Okun (variable) vs.	2.37	-5.39	-1.95	**5.44**	0.45	

1 year ahead - 2nd period	Naïve 1	Naïve 2	AR	Okun (fixed)		Okun (variable)
				Static	Dynamic	
Naïve 1 vs.		1.69	2.70	**10.37**	7.74	**9.32**
Naïve 2 vs.	-1.69		-0.64	**6.69**	7.21	**8.14**
AR vs.	-2.70	0.64		**8.10**	6.86	**9.30**
Okun (fixed) – static vs.	**-10.37**	**-6.69**	**-8.10**		**-2.67**	0.94
Okun (fixed) – dynamic vs.	-7.74	-7.21	-6.86	**2.67**		**5.69**
Okun (variable) vs.	**-9.32**	**-8.14**	**-9.30**	-0.94	**-5.69**	

2 years ahead - 1st period	Naïve 1	Naïve 2	AR	Okun (fixed)		Okun (variable)
				Static	Dynamic	
Naïve 1 vs.		**-2.32**	-0.48	2.99	-0.57	-0.89
Naïve 2 vs.	**2.32**		**4.53**	**3.47**	**3.89**	**3.23**
AR vs.	0.48	**-4.53**		1.14	1.59	1.74
Okun (fixed) – static vs.	-2.99	**-3.47**	-1.14		-1.49	-2.97
Okun (fixed) – dynamic vs.	0.57	**-3.89**	-1.59	1.49		0.02
Okun (variable) vs.	0.89	**-3.23**	-1.74	2.97	-0.02	

2 years ahead - 2nd period	Naïve 1	Naïve 2	AR	Okun (fixed)		Okun (variable)
				Static	Dynamic	
Naïve 1 vs .		10.33	9.72	27.52	18.57	**21.99**
Naïve 2 vs.	-10.33		-5.18	0.39	0.97	**4.66**
AR vs.	-9.72	5.18		6.00	7.60	**10.25**
Okun (fixed) – static vs.	-27.52	-0.39	-6.00		-0.37	**9.85**
Okun (fixed) – dynamic vs.	-18.57	-0.97	-7.60	0.37		**8.71**
Okun (variable) vs.	**-21.99**	**-4.66**	**-10.25**	**-9.85**	**-8.71**	

Null Hypothesis: Forecast accuracy is equal. Alternative Hypothesis: Forecast accuracy is different. A negative value of average S(1) indicates that the method in the first column is better than the competing one while a positive value of average S(1) indicates the opposite. Highlighted cells indicate a rejection of the null hypothesis at the 0.05 significance level.

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where $S_i(1)$ is the value of the Diebold-Mariano statistic for region i and N is the total number of regions (17, in our case). The panel Diebold-Mariano test also has a standard normal limiting distribution. As we can see from table 6, the Okun model with fixed coefficient provides the best accuracy for 1 year ahead forecasts both in the first and the second period. In the second period, we cannot reject that the accuracy of the Okun model with time varying coefficient is also similar. This result does not hold, however, when we look at 2 years ahead forecasts. In this case, the best model for the first period is the naïve method assuming that growth rates are constant, but for the second period the Okun model with time varying coefficient is found to be the best. Although we cannot generalise, this evidence shows that this more flexible specification can be better suited for forecasting in the presence of structural change or recent changes in the business cycle dynamics.

5. Concluding remarks

The objective of the paper was to analyse the possibility of improving the forecasts for regional unemployment rates in Spain using a time-varying coefficient specification of the Okun's law. With this aim, we have carried out a forecasting competition in two time periods characterized by different macroeconomic conditions. The obtained results allow us to conclude that, in general, the consideration of models based on the Okun's law improve the forecasting performance in nearly all regions, particularly when the time-varying coefficient specification is used. However, the accuracy of the models is not good enough to provide reliable forecasts in real-time forecasting exercises for Spanish regions. Difficulties in order to obtain accurate forecasts of the Spanish aggregate unemployment rate have already been highlighted in the previous literature (see, for instance, Olmedo, 2011). Future research could expand into two directions: first, the consideration of non-linearities; and, second, the development of more sophisticated tools trying to better capture the complex relationship between unemployment, economic activity and other factors (i.e., macroeconometric forecasting models).

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