Forecasting Unemployment Rates with International Factors

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Abstract

In this paper we study international linkages when forecasting unemployment rates in a sample of 24 OECD economies. We propose a Global Unemployment Factor (GUF) and test its predictive ability considering in-sample and out-of-sample exercises. Our main results indicate that the predictive ability of the GUF is heterogeneous across countries. In-sample results are statistically significant for Austria, Belgium, Czech Republic, Finland, France, Ireland, The Netherlands, Portugal, Slovenia, Sweden and United States. Robust statistically significant out-of-sample results are found for Belgium, Czech Republic, France, The Netherlands, Slovenia, Sweden and the United States. This means that the inclusion of the GUF adds valuable information to predict domestic unemployment rates, at least for these last seven countries.

JEL Codes: J60, J64, J01, F22, F44, F47, F43, F41, E24, E27, E32, E37

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1. Introduction

In this paper we show that a Global Unemployment Factor (GUF) is useful to forecast local unemployment rates in a number of developed economies. Results are robust to different sample periods in both in-sample and out-of-sample analyses.

Improving the accuracy of unemployment rate forecasts is fundamental to develop appropriate policies or to make right decisions regarding the labor market. After the last world's financial crisis, the anticipation of unemployment rates has become more important because of its relevance and usefulness in different sectors. Policy makers and governmental entities may consider forecasts of unemployment as a proxy to measure the performance of unemployment mitigation policies, and banks may consider them as a proxy of credit paybacks. If they see a high unemployment rate in the future, they can limit bank loans as a result of the expectation of people being unemployed and with no salaries.

International interdependencies across countries have been long analyzed in the literature. In the case of inflation, for instance, several papers explore the predictive linkages between international and domestic prices. See, for instance, Ciccarelli and Mojon (2010), Pincheira and Gatty (2016) and Medel, Pedersen and Pincheira (2016). Nevertheless, to our knowledge, our paper is the first analyzing whether an international measure of unemployment may have the ability to predict domestic ones.

Unemployment is an important macroeconomic indicator, with implications in many other areas. It affects salaries and therefore the pensions received by people after their working life. It also affects population welfare and, consequently, economic well-being (see Ford, Clark, McManus, Jarris, Jenkins, Bebbington, Brugha, Meltzer and Stansfeld 2010). These issues have direct public policy implications.

There are some interesting papers in the forecasting literature focusing on unemployment rates. For instance, Franses, Paap and Vroomen (2004) present a non-linear model to forecast Canadian and United States unemployment rates. They compare their results with Auto-Regressive (AR) linear and non-linear specifications. They find that AR parameters vary in the recessions and these are more stable through economic expansions. Milas and Rothman (2008) use Smooth Transition Vector Error-Correction Models (STVECMs) to forecast unemployment rates for United States, United Kingdom, Canada and Japan. They find that out-of-sample results from the pooled-median forecasting approach are better for USA, U.K. and Canada, and that Mean Squared Prediction Errors (MSPE) show a significant reduction, relative to linear models, for the U.S. and the U.K. Also, STVCEM forecasts seem to behave better during expansions of the business cycle in the U.S, thus improving the accuracy of the forecasts for unemployment rate. Askitas and Zimmermann (2009) focus on the different variables used to forecast the unemployment rate in Germany, suggesting the use of google search queries as an additional source of information to increase forecasting accuracy. Barnichon and Nekarda (2012) introduce work flows to forecast unemployment. The major conclusion of their work is that models based on labor force flows improve dramatically the accuracy of forecasts. More recently Jalles (2017), acknowledging the importance of business cycle behavior, asseses the evaluation of unemployment forecasts in general and in particular turning points. To do this, he takes private's sector unemployment rate forecasts for 9 advanced economies between September 1989 and October 2012 brought together by Consensus Economics. His study focuses on answering seven questions, within which are: i) how do forecasts statistically behave among countries and in time, ii) which robustness analyses can be performed at different horizons, iii) are forecasts accurate during recession and recovery episodes, iv) is unemployment sub or over-predicted and for how long. His results suggest that unemployment forecasts are biased to over-prediction and inefficient.

To our knowledge, however, there are no studies explicitly accounting for international linkages in unemployment. So, as a novel way to address this gap in the literature, we introduce a Global Unemployment Factor (GUF) to evaluate if this variable may improve the accuracy of domestic unemployment forecasts given by a benchmark model. We carry out in-sample and out-of-sample analyses to test the predictive relevance of the GUF using data for OECD economies, distinguishing pre and post Subprime Crisis periods to test the robustness of our results.

Our main findings indicate that the predictive ability of the leave-one-out GUF is heterogeneous across countries. In-sample results are statistically significant for Austria, Belgium, Czech Republic, Finland, France, Ireland, The Netherlands, Portugal, Slovenia, Sweden and United States. Robust statistically significant out-of-sample results are found for Belgium, Czech Republic, France, The Netherlands, Slovenia, Sweden and the United States. This means that the inclusion of the GUF adds valuable information to predict domestic unemployment rates for, at least, these last seven countries.

The rest of the paper is organized as follows. In section 2 we present our data and forecasting models. In section 3 we present and discuss our in-sample and out-of-sample results. Finally, in section 4 we present a summary of our results and our main conclusions.

2. Data and Econometric Set-up

We consider seasonally adjusted unemployment rate series for 24 countries, retrieved from the Organization for Economic Cooperation and Development (OECD). Data is harmonized. According to the definition given by the OECD, "*harmonized unemployment rates define the unemployed as people of working age who are without work, are available for work, and have taken specific steps to find work. The uniform application of this definition results in estimates of unemployment rates that are more internationally comparable than estimates based on national definitions of unemployment. This indicator is measured in numbers of unemployed people as a percentage of the labor force and it is seasonally adjusted. The labor force is defined as the total number of unemployed people plus those in civilian employment*"[2].

We consider observations from January 1998 to September 2017 (229 obs). We also consider one-month LIBOR series and the Industrial Production Index (IPI) for each country. These series are taken from the FRED database. Finally, we consider a dummy for the Subprime Crisis, which takes a value of 1 from June 2008 to June 2009, and 0 in the rest of the sample period.

Monthly observations of these variables are available for the following countries:

Table 1: Sample of Countries

Austria	France	Korea	Slovak Republic
Belgium	Germany	Luxembourg	Slovenia
Canada	Hungary	Netherlands	Spain
Czech Republic	Ireland	Norway	Sweden
Denmark	Italy	Poland	United Kingdom
Finland	Japan	Portugal	United States

Appendix A shows descriptive statistics of unemployment and industrial production series.

With traditional unit root tests (Augmented Dickey-Fuller and Phillips-Perron) we cannot reject the existence of unit roots in our unemployment series at usual statistical levels[3]. Consequently, our models are specified in first differences. For these specifications, the null hypothesis of a unit root was consistently rejected at a 1% and 5% significance levels for all our countries.

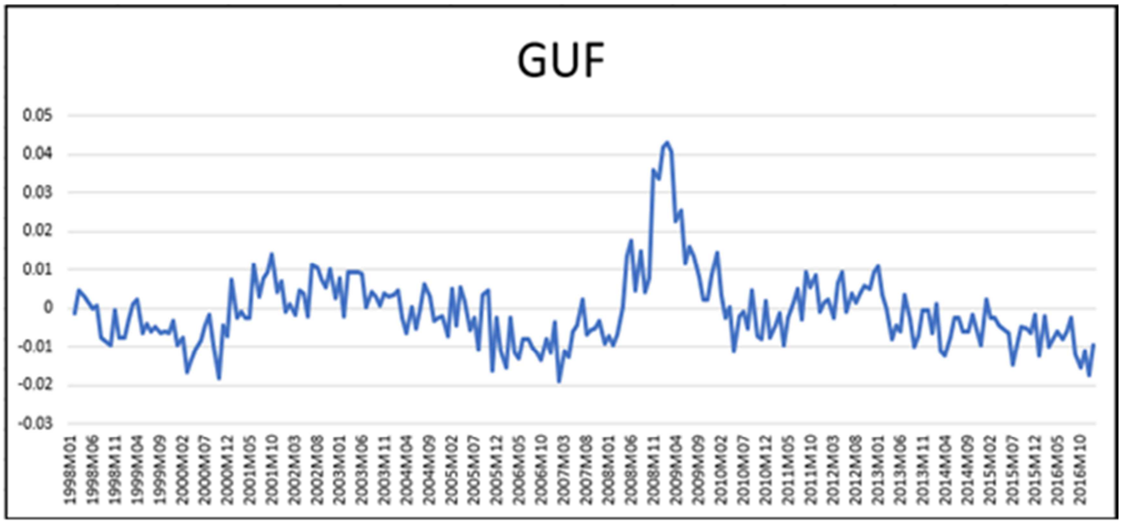
To test the existence of international linkages in unemployment rates, we introduce the GUF. This variable is constructed as the unweighted average of the first difference of the natural

[2] See https://data.oeced.otg/unemp/harmonised-unemployment-rate-hur.htpm.

[3] Tables available upon request.

logarithm of our monthly unemployment rate series for the countries in our sample. As expected, it shows higher values for the last great financial recession (Subprime Crisis). During this period, the world witnessed a severe decay in the output of many developed economies, which led to atypical rises in unemployment rates consistent with Figure 1.

Figure 1: The Global Unemployment Factor



Notes: The GUF from this figure is calculated as the unweighted average of the first difference of the natural logarithm of our monthly unemployment rate series for the 24 countries in our sample. Source: Author's elaboration.

To avoid double counting, we use a leave-one-out version of the GUF. For example, the GUF used to predict domestic unemployment in the first country of our sample is calculated as follows:

$$GUF_{1,t} = 1/23(Z_{2,t} + Z_{3,t} + Z_{4,t} + \ldots + Z_{24,t})$$

where $Z_{i,t}$, with i = 2, 3, 4, ..., 24, represents the log first difference of the monthly unemployment rate for country "i", excluding the first one.

Table B1 in Appendix B shows the correlation coefficient between the leave-one-out GUF and the monthly unemployment series for each country in the sample. They are all nonnegative. We also can see that for 15 countries, the correlation coefficient is higher than 0.3. Furthermore, for Czech Republic, Finland, France, Germany, The Netherlands and Spain, this number is above 0.4, showing a non-negligible correlation level between these two series.

Our approach considers the comparison of forecasts coming from two nested models:

Model 1

$$Z_{t+h} - Z_t = \alpha^{(h)} + \sum_{i=0}^{p_h} \beta_i^{(h)} [Z_{t-i} - Z_{t-h-i}] + \gamma^{(h)} CS_t + \sum_{i=0}^{q_h} \delta_i^{(h)} [IPI_{t-i} - IPI_{t-h-i}] + \sum_{i=0}^{r_h} \tau_i^{(h)} [LIBOR_{t-i} - LIBOR_{t-h-i}] + \sum_{i=0}^{s_h} \mu_i^{(h)} \left[IPI_{USA,t-i} - IPI_{USA,t-h-i}\right] + \varepsilon_{t+h}^{(h)}$$

Model 2

$$Z_{t+h} - Z_t = \alpha^{(h)} + \sum_{i=0}^{p_h} \beta_i^{(h)} [Z_{t-i} - Z_{t-h-i}] + \gamma^{(h)} CS_t + \sum_{i=0}^{q_h} \delta_i^{(h)} [IPI_{t-i} - IPI_{t-h-i}] + \sum_{i=0}^{r_h} \tau_i^{(h)} [LIBOR_{t-i} - LIBOR_{t-h-i}] + \sum_{i=0}^{s_h} \mu_i^{(h)} \left[IPI_{USA,t-i} - IPI_{USA,t-i}\right] + \sum_{i=0}^{w_h} \rho_i^{(h)} [GUF_{t-i} - GUF_{t-h-i}] + \varepsilon_{t+h}^{(h)}$$

Here Z is the natural logarithm of the unemployment rate, CS is the dummy associated to the Subprime Crisis, IPI is the country-specific industrial production index, IPIUSA represents the industrial production index of United States, *h* represents the forecasting horizon, which in our empirical application will be equal to 1 (h=1) whereas p_h, q_h, r_h, s_h and w_h represent the maximum lag length of [Zt-i - Zt-h-i], [IPIt-i - IPIt-h-i], [LIBORt-i - LIBORt-h-i], [IPIUSAt-i – IPIUSAt-h-i] and [GUFt-i - GUFt-h-i], respectively. $\varepsilon_{t+h}^{(h)}$ represents an error term. p_h, q_h, r_h, s_h and w_h are selected automatically using BIC. We allow these lag lengths to differ, but in the same range of 1 to 12. We first select $p_h = p_{h0}$, $q_h = q_{h0}$, $r_h = r_{h0}$ and $s_h = s_{h0}$ in Model 1, and use the same lag order for them in Model 2. Once p_h is set to p_{h0}, q_h is set to q_{h0}, r_h to r_{h0} and s_h to s_{h0} in Model 2, we select the parameter w_h. With this strategy, we make sure that Model 1 is nested in Model 2. From now on, we will refer to Model 1 as the nested or the benchmark model, and to Model 2 as the nesting model or the model containing the excess parameter(s) $\rho_i^{(h)}$.

Models 1 and 2 are estimated via OLS. Inference is conducted using HAC standard errors according to Newey and West (1987) with automatic lag length selection according to Newey and West (1994).

In the in-sample evaluation we test for the relevance of the leave-one-out GUF with a standard Wald test. Notice that the Null and Alternative Hypotheses are the same in both in-sample and out-of-sample evaluations. These hypotheses look as follows:

$$H_0: \rho_0 = \rho_1 = \ldots = \rho_w = 0$$

$$H_1: \rho_0 \neq 0 \text{ or } \rho_1 \neq 0 \text{ or } \ldots \rho_w \neq 0$$

In the out-of-sample evaluation we test for the relevance of the leave-one-out GUF with the ENCNEW test developed by Clark and McCracken (2001). This test is frequently used in the forecasting literature, especially considering unstable environments. See for instance Chen, Rossi and Rogoff (2010, 2014) and Pincheira and Hardy (2019a, 2019b, 2018).

The ENCNEW test has a non-standard asymptotic distribution under the null hypothesis, but critical values for one-step-ahead forecasts are tabulated in Clark and McCracken (2001). The asymptotic distribution of the ENCNEW test under the null hypothesis is a functional of Brownian motions depending on the number of excess parameters of the nesting model, the scheme used to update the estimates of the parameters (rolling, recursive or fixed), and the parameter π defined as the limit of the ratio P/R, where P is the number of one-step-ahead forecasts and R is the size of the first estimation window used in the out-of-sample analysis[4].

For our in-sample analysis we estimate the parameters with all the available observations. In contrast, for the out-of-sample analysis, we split the sample in two windows: an initial estimation window of size R and a prediction window of size P such that $P + R = T$, where T is the total number of observations. For robustness, we split our sample in four different ways considering the following ratios:

P/R = 3.58 P/R = 1.29 P/R = 0.59 P/R = 0.20

Finally, it is important to mention that we use a rolling scheme to update the estimates of our parameters in the out-of-sample analysis. We think that a rolling scheme is more adequate than an expansive scheme to capture the potential instabilities that are likely to be present in the data.

3. Empirical Results

In this section we start by reporting in-sample estimates and tests of specification 1. Afterwards, we report results of the ENCNEW out-of-sample test of Clark and McCracken (2001).

3.1 In–Sample Analysis

Tables 2.1 to 2.4 show estimates of our models for each country as described in section 2. We also report HAC standard errors according to Newey and West (1987, 1994). Each table contains the coefficients and standard errors corresponding to the covariates considered in the models. Statistical significance for each of the coefficient estimates is shown in the tables (*p<10%,

[4] See Clark and McCracken (2001) or West (2006) for further details about out-of-sample evaluations in nested environments.

**p<5%, ***p<1%) and standard errors are given in parenthesis. Additionally, in the last row of each table, we report the p-value of the Wald test statistic associated to the null hypothesis that the coefficients of the leave-one-out GUF are equal to zero.

Table 2.1: In-sample results when forecasting monthly unemployment rates

	Austria	Belgium	Canada	Czech Republic	Denmark	Finland
$Z_{i,t-1}$	0.419***	0.572***	-0.115**	0.07	0.207**	0.414***
	(0.066)	(0.0578)	(0.0511)	(0.0758)	(0.0861)	(0.0527)
$Z_{i,t-2}$	-0.289***	-0.1584**		0.369***	0.173*	
	(0.0675)	(0.0701)		(0.0734)	(0.0922)	
$Z_{i,t-3}$		-0.363***			-0.343***	
		(0.0581)			(0.1032)	
CS	0.009	0.005	0.012	0.003	0.0365***	0.006**
	(0.0096)	(0.0074)	(0.0084)	(0.0065)	(0.0094)	(0.0026)
$IPI_{i,t-1}$	-0.36***	0.044	0.2	-0.147	0.092*	-0.008
	(0.1067)	(0.0688)	(0.1357)	(0.1126)	(0.0535)	(0.026)
$IPI_{i,t-2}$				-0.183***		
				(0.0669)		
$LIBOR_{t-1}$	0.043***	0.005	-0.033***	-0.008	-0.018*	-0.002
	(0.0125)	(0.0102)	(0.011)	(0.0117)	(0.0109)	(0.0038)
$IPI_{USA,t-1}$	-0.039	0.3558**	-0.51**	0.065	0.301	-0.163**
	(0.2742)	(0.1742)	(0.2092)	(0.2004)	(0.4491)	(0.0757)
$IPI_{USA,t-2}$			-0.592*			
			(0.3321)			
$GUF_{i,t-1}$	0.61***	0.651***	0.14	0.63***	0.539	0.192**
	(0.2338)	(0.1753)	(0.1032)	(0.2424)	(0.378)	(0.0766)
Constant	0.0017	-0.0012	-0.0013	-0.0007	-0.0012	-0.0009
	(0.0019)	(0.0016)	(0.0012)	(0.0019)	(0.0024)	(0.0006)
Observations	226	225	226	226	225	227
R^2	0.2823	0.4837	0.203	0.401	0.2973	0.4595
Wald Test p-value	0.0091	0.0002	0.1754	0.0093	0.1542	0.0123

Notes: Standard errors are shown in parenthesis. *p < 10%, **p < 5%, ***p < 1%. Source: Author's elaboration.

Table 2.2: In-sample results when forecasting monthly unemployment rates

	France	Germany	Hungary	Ireland	Italy	Japan
$Z_{i,t-1}$	0.313***	0.052	0.484***	0.546***	-0.1632***	-0.154**
	(0.0579)	(0.0711)	(0.0589)	(0.0735)	(0.0557)	(0.061)
$Z_{i,t-2}$	0.134*	0.334***		0.179**	0.124**	-0.182**
	(0.0701)	(0.072)		(0.0895)	(0.0617)	(0.0759)

$Z_{i,t-3}$		0.228***		-0.451***	-0.002	0.137**
		(0.0748)		(0.0762)	(0.098)	(0.0622)
$Z_{i,t-4}$				-0.012	0.201***	
				(0.0752)	(0.0594)	
$Z_{i,t-5}$				0.206***		
				(0.0688)		
CS	-0.0003	-0.004	0.007	0.023**	-0.004	0.014
	(0.0034)	(0.004)	(0.0055)	(0.0103)	(0.007)	(0.0093)
$IPI_{i,t-1}$	-0.035	-0.114***	-0.05	-0.036*	-0.136	-0.011
	(0.0395)	(0.0394)	(0.0388)	(0.0186)	(0.1211)	(0.0593)
$IPI_{i,t-2}$		-0.104***				
		(0.0358)				
$LIBOR_{t-1}$	-0.003	-0.002	-0.013	0.001	0.001	-0.035**
	(0.0029)	(0.0037)	(0.0089)	(0.01)	(0.011)	(0.0166)
$LIBOR_{t-2}$					-0.037***	
					(0.0112)	
$IPI_{USA,t-1}$	-0.04	-0.017	0.16	-0.163	0.127	-0.098
	(0.0687)	(0.1008)	(0.1511)	(0.2159)	(0.1993)	(0.4388)
$IPI_{USA,t-2}$	-0.243***					
	(0.0706)					
$GUF_{i,t-1}$	0.224***	0.14	0.183	0.382*	0.206	0.279
	(0.0737)	(0.0944)	(0.1205)	(0.1954)	(0.1882)	(0.2417)
Constant	-0.0003	-0.001	-0.002*	-0.001	-0.0002	-0.002
	(0.0006)	(0.0007)	(0.0011)	(0.0015)	(0.0015)	(0.0019)
Observations	226	225	227	223	224	225
R^2	0.4224	0.4117	0.3449	0.5868	0.1739	0.1462
Wald Test p-value	0.0024	0.1381	0.1291	0.0504	0.2731	0.2476

Notes: HAC standard errors are estimated according to Newey and West (1987, 1994). $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source: Author's elaboration.

Table 2.3: In-sample results when forecasting monthly unemployment rates

	Korea	Luxembourg	Netherland	Norway	Poland	Portugal
$Z_{i,t-1}$	-0.102	-0.067	0.056	0.148**	0.814***	0.341***
	(0.0861)	(0.0772)	(0.0682)	(0.066)	(0.0498)	(0.0581)
$Z_{i,t-2}$	-0.056	0.202***	0.362***	0.08		
	(0.0611)	(0.076)	(0.0792)	(0.068)		
$Z_{i,t-3}$	-0.019	0.339***	0.187**	-0.201***		
	(0.0573)	(0.073)	(0.0749)	(0.0648)		
$Z_{i,t-4}$	-0.216***	0.228***		0.204***		
	(0.0696)	(0.0619)		(0.0605)		
$Z_{i,t-5}$	0.083*					

	(0.0463)					
$Z_{i,t-6}$	0.134**					
	(0.0525)					
CS	0.019	-0.0095	-0.015***	0.0028	0.0018	0.006
	(0.0135)	(0.0068)	(0.0046)	(0.0122)	(0.0056)	(0.0055)
$IPI_{i,t-1}$	0.024	0.083**	-0.085*	-0.042	-0.008	-0.005
	(0.1188)	(0.0414)	(0.0467)	(0.0614)	(0.0442)	(0.0437)
$LIBOR_{t-1}$	0.037**	-0.019**	-0.006	0.022	-0.0038	-0.0052
	(0.0185)	(0.0089)	(0.0046)	(0.0158)	(0.0048)	(0.0077)
$LIBOR_{t-2}$		-0.028***	0.0097			
		(0.0102)	(0.0059)			
$LIBOR_{t-3}$			-0.021***			
			(0.0056)			
$IPI_{USA,t-1}$	-0.424	-0.1605	-0.343***	-0.2186	-0.0089	0.428**
	(0.6348)	(0.1798)	(0.1305)	(0.3106)	(0.128)	(0.2078)
$GUF_{i,t-1}$	0.217	-0.109	-0.051	0.467	0.015	0.376**
	(0.3942)	(0.1925)	(0.1739)	(0.2971)	(0.1015)	(0.1578)
$GUF_{i,t-2}$			0.609***			
			(0.1375)			
Constant	-0.005	0.001	0.0013	0.0013	-0.0007	0.0008
	(0.0033)	(0.0016)	(0.001)	(0.0023)	(0.0006)	(0.0015)
Observations	222	224	225	224	227	227
R^2	0.1136	0.2953	0.4737	0.131	0.6761	0.2054
Wald Test p-value	0.5824	0.5704	0	0.1139	0.8859	0.0173

Notes: HAC standard errors are estimated according to Newey and West (1987, 1994). $*p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$. Source: Author's elaboration.

Table 2.4: In-sample results when forecasting monthly unemployment rates

	Slovak Republic	Slovenia	Spain	Sweden	United Kingdom	United States
$Z_{i,t-1}$	0.737***	0.487***	0.685***	-0.631***	0.162*	-0.207***
	(0.0742)	(0.0536)	(0.0724)	(0.0768)	(0.0843)	(0.0631)
$Z_{i,t-2}$		0.173***	0.006	-0.386***		0.073
		(0.0577)	(0.006)	(0.0683)		(0.082)
$Z_{i,t-3}$		-0.247***				0.091*
		(0.0906)				(0.0508)
$Z_{i,t-4}$						0.012
						(0.0543)

$Z_{i,t-5}$						0.277***
						(0.0735)
$Z_{i,t-6}$						0.209***
						(0.071)
CS	0.003	-0.009		0.03**	0.016***	0.0217**
	(0.0072)	(0.0055)		(0.0143)	(0.0047)	(0.0104)
$IPI_{i,t-1}$	-0.038**	-0.103*	-0.154**	0.019	-0.168	-0.358
	(0.0185)	(0.0549)	(0.06)	(0.1473)	(0.1139)	(0.232)
$IPI_{i,t-2}$		-0.191**	-0.102			
		(0.0867)	(0.0622)			
$IPI_{i,t-3}$		-0.178***				
		(0.0594)				
$LIBOR_{t-1}$	-0.012***	0.016	-0.0075	0.01	-0.0012	-0.022**
	(0.0046)	(0.0153)	(0.0067)	(0.0164)	(0.0072)	(0.009)
$IPI_{USA,t-1}$	0.104	-0.13	-0.045	0.258	-0.322**	
	(0.1321)	(0.138)	(0.182)	(0.467)	(0.1464)	
$GUF_{i,t-1}$	0.042	0.54***	-0.04	1.664***	0.187	0.419**
	(0.0927)	(0.1705)	(0.121)	(0.263)	(0.1356)	(0.2075)
$GUF_{i,t-2}$						0.571**
						(0.2214)
$GUF_{i,t-3}$						-0.538*
						(0.2922)
$GUF_{i,t-4}$						-0.755***
						(0.2441)
Constant	-0.0007	0.002*	-0.0004	-0.003	-0.002	-0.001
	(0.0007)	(0.001)	(0.0007)	(0.0029)	(0.0012)	(0.0017)
Observations	227	225	226	226	227	222
R^2	0.6178	0.465	0.6639	0.371	0.2528	0.3571
Wald Test p-value	0.6482	0.0016	0.7388	0	0.1687	0.0003

Notes: HAC standard errors are estimated according to Newey and West (1987, 1994). *p<0.1, ** p<0.05, *** p<0.01.
Source: Author's elaboration.

Results in Tables 2.1-2.4 show that the leave-one-out GUF is statistically significant in almost a half of the countries in our sample: 11 out of the total of 24 countries, implying that this measure of global unemployment could help forecast local rates in a substantial share of our economies. In fact, when inference is carried out at the 10% significance level, the null hypothesis that the coefficients associated to the GUF are zero, is rejected for Austria, Belgium, Czech Republic, France, Ireland, Finland, Netherlands, Portugal, Slovenia, Sweden and the United States.

For most of the countries in our sample the BIC chooses only one lag of the GUF. As a matter of fact, in only two countries the BIC chooses a distributed lag structure for the GUF. These countries are the Netherlands and the USA. In these two cases we see opposite signs in different lags of the GUF, which does not have a simple interpretation. In the majority of the 22 countries in which only the first lag of the GUF is included, the corresponding coefficient is positive, indicating that an uprise in global unemployment predicts an uprise in local unemployment as well. The only two countries displaying negative coefficients are Luxembourg and Spain. Neither of these two coefficients are statistically significant, however.

In is also interesting to remark that consistent with the results found in Jalles (2017), Tables 2.1-2.4 show a substantial dependence of French, Canadian and UK unemployment rates with USA indicators (USA IPI in this context). This also happens in the case of Belgium, Finland, Netherlands and Portugal.

In summary, our in-sample analysis suggests that the leave-one-out GUF has the ability to forecast local rates for 11 countries. Moreover, an increase in the GUF predicts an increase in local unemployment rates, which is a fairly intuitive result. In-sample analyses, however, are prone to overfitting. To mitigate this shortcoming, we show next the results of an out-of-sample analysis that for simplicity is focused on one-step-ahead forecasts only, leaving the analysis for longer horizons as an extension for further research.

3.2 Out–of-Sample Analysis

Table 3 shows results for the ENCNEW test proposed by Clark and McCracken (2001), considering four different values of the ratio P/R, where P denotes the number of one-step-ahead forecasts and R denotes the size of the rolling windows used in the out-of-sample exercises. Notice that a high value of the ratio P/R indicates that a large number of forecasts are constructed with parameters that are estimated in small rolling windows of size R. Similarly, a low value of the ratio P/R indicates that a relatively low number of forecasts are constructed with parameters that are estimated in large rolling windows of size R.

Table 3 shows robust results in favor of the ability that the leave-one-out GUF has to predict unemployment rates in Belgium, Czech Republic, France, The Netherlands, Sweden, USA and Slovenia. For these countries the ENCNEW test rejects the null in the four different out-of-sample exercises we carry out for different values of the ratio P/R. Interestingly, this set of countries is a subset of the countries in which the GUF was statistically significant in our in-sample analyses reported in Tables 2.1-2.4. So, in summary, our out-of-sample results are roughly consistent with our in-sample results.

Table 3 also shows really poor results for Canada, Korea, Norway and Slovak Republic, as in none of the four out-of-sample exercises for different values of the ratio P/R we are able to reject the null hypothesis. This is again consistent with our in-sample results shown in Tables 2.1-2.4. Let us recall that in those tables the null hypothesis of zero coefficients associated with the GUF was not rejected for these countries according to a standard Wald test.

For the rest of the countries, not mentioned in the two precedent paragraphs, the evidence is mixed or unstable. This means that with the ENCNEW test we are able to reject the null in at least one of the out-of-sample exercises we carry out for different values of the ratio P/R, but not in all four of them.

Table 3: **Forecasting Unemployment Rates with International Factors**.

Out-of-Sample Analysis with the ENCNEW Test

	ENCNEW			
	P/R = 3.58	P/R = 1.29	P/R = 0.59	P/R = 0.20
Austria	-0.41	1.52*	-0.2	0.77*
Belgium	13.78***	10.4***	2.15**	0.59*
Canada	-3.89	-0.04	-0.01	0.02
Czech Republic	27.18***	12.28***	6.78***	2.03***
Denmark	-4.77	2.41**	0.46	0.74*
Finland	12.5***	9.78***	1.28*	-2.6
France	10.67***	5.6***	3.71***	1.85***
Germany	7.85***	-0.72	0.46	0.53*
Hungary	3.2*	-1.4	-0.34	-0.23
Ireland	15.08***	-1.41	-0.41	0.95**
Italy	4.31**	1.4	0.58	0.36
Japan	4.74**	0.94	0.62	-0.36
Korea	0.37	-1.53	-0.59	-0.45

Luxembourg	5.79**	-2.53	-1.19	-1.36
Netherlands	11.89***	5.71***	4.87***	4.99***
Norway	1.75	1.37	0.88	-0.08
Poland	-0.48	-0.75	0.66	0.77*
Portugal	2.57*	1.38	0.88	0.43
Slovak Republic	-3.47	-1.07	-0.11	0.02
Slovenia	3.25*	6.8***	4.37***	4.66***
Spain	12.69***	1.09	-0.91	-0.65
Sweden	32.81***	22.05***	11.14***	5.93***
United Kingdom	1.35	1.19	0.37	0.51*
United States	8.56**	12.89***	4.84***	3.03***

Notes: P is the number of one-step-ahead forecasts, R the sample size of the first estimation window. The table reports the ENCNEW test of Clark and McCracken (2001). We use the critical values reported in that paper. *p<0.1, ** p<0.05, *** p<0.01. Source: Author's elaboration.

3.3 Forecast Accuracy

In section 3.2 we have carried out inference to compare the population MSPE of the models including the GUF with the population MSPE of the same models but excluding our international factor. Nevertheless, due to sampling error, the model displaying the lowest MSPE at the population level, may not necessarily be displaying the lowest MSPE at the sample level. For this reason, we study the out-of-sample R^2 according to the definition used by Goyal and Welch (2008), and check if there are gains in terms of MSPE at the sample level using the leave-one-out GUF.

Goyal and Welch R^2 is defined as follows:

$$\text{Out-of-sample } R^2 = 1 - (MSPE_L / MSPE_S)$$

where $MSPE_L$ denotes the out-of-sample mean squared prediction error of the model including our international factor and $MSPE_S$ denotes the out-of-sample mean squared prediction error of the model excluding this factor. Notice here that these terms are measured at the sample level. This means that both $MSPE_L$ and $MSPE_S$ are constructed in our out-of-sample exercises with OLS estimates of the population parameters of the models. If this R^2 coefficient takes a negative value, it indicates that the model excluding the leave-one-out GUF outperforms the model which includes this global factor. An out-of-sample R^2 equal to zero indicates that both models produce similar forecasts and a positive value indicates that the model with the GUF outperforms the model without the international factor.

Table 4 shows out-of-sample R^2 computed in the four out-of-sample exercises with different values of the ratio P/R. Table 4 also shows in-sample R^2 for comparison. Some interesting features of Table 4 are worth mentioning. First, out-of-sample R^2 tend to be much smaller than their in-sample counterparts; this is consistent with a vast literature reporting discrepancies between in-sample and out-of-sample forecast evaluations in this direction: less evidence of predictability is found out-of-sample relative to in-sample evaluations. Second, many of the entries in Table 4 are negative, indicating in these cases that at the sample level the inclusion of the GUF does not increase predictability. Interestingly, there are five countries for which robust positive out-of-sample R^2 are obtained in all four exercises with different values of the ratio P/R. These countries are Czech Republic, France, The Netherlands, Slovenia and Sweden. This is consistent with the results shown with the ENCNEW test in section 3.2, because this is a subset of countries for which the ENCNEW test detected predictability at the population level when using the GUF.

Table 4: In-Sample and Out-of-Sample R^2 when Forecasting Unemployment Rates with an International Unemployment Factor

	In-sample R^2	Out-of-sample R^2			
		P/R = 3.58	P/R = 1.29	P/R = 0.58	P/R = 0.2
Austria	0.28	-0.035	-0.007	-0.026	-0.002
Belgium	0.48	0.075	0.065	0.003	-0.022
Canada	0.203	-0.057	-0.003	-0.001	-0.001
Czech Republic	0.401	0.136	0.071	0.057	0.056
Denmark	0.2973	-0.102	0.012	-0.034	0.013
Finland	0.4595	0.058	0.055	-0.05	-0.231

France	0.4224	0.059	0.042	0.044	0.056
Germany	0.4117	0.033	-0.038	-0.005	-0.027
Hungary	0.3449	-0.0002	-0.038	-0.012	-0.014
Ireland	0.5868	0.013	-0.132	-0.038	0.023
Italy	0.1739	-0.024	0.012	0.01	0.016
Japan	0.1462	-0.002	-0.005	-0.003	-0.035
Korea	0.1136	-0.039	-0.031	-0.016	-0.025
Luxembourg	0.2953	0.013	-0.07	-0.043	-0.086
Netherlands	0.4737	0.05	0.023	0.053	0.154
Norway	0.131	-0.023	-0.005	0.003	-0.021
Poland	0.6761	-0.015	-0.016	0.012	0.035
Portugal	0.2054	-0.038	-0.014	0.005	0.006
Slovak Republic	0.6178	-0.064	-0.018	-0.005	-0.001
Slovenia	0.465	0.001	0.07	0.074	0.163
Spain	0.6639	0.022	-0.019	-0.051	-0.044
Sweden	0.371	0.142	0.132	0.072	0.122
United Kingdom	0.2528	-0.017	0.012	0.007	0.024
United States	0.3571	-0.1002	0.059	0.025	0.102

Notes: P represents the number of one-step-ahead forecasts, R the sample size of the first estimation window. Out-of-sample R^2 is constructed inspired in Goyal and Welch (2008). Source: Authors' elaboration.

4. Concluding Remarks

In this paper we study international linkages when forecasting unemployment rates in a sample of 24 OECD economies. Specifically, we propose a Global Unemployment Factor (GUF) and test its predictive ability considering in-sample and out-of-sample exercises. We control for the subprime crisis, other determinants of domestic unemployment, and consider four different estimation windows for robustness. To test for predictability out-of-sample, we rely on the ENCNEW test proposed by Clark and McCracken (2001).

Our results show that the predictive ability of the leave-one-out GUF is heterogeneous across countries. In-sample results are statistically significant for Austria, Belgium, Czech Republic, Finland, France, Ireland, The Netherlands, Portugal, Slovenia, Sweden and United States. Robust statistically significant out-of-sample results are found for Belgium, Czech Republic, France, The Netherlands, Slovenia, Sweden and the United States. This means that the inclusion of the GUF adds valuable information to predict domestic unemployment rates, at least for these last seven countries.

The reasons behind our findings involve several possible explanations including migration flows, country-specific labor market features and common business cycles, amongst others. Beyond the particular reasons behind our findings, our results suggest that the GUF should be seriously taken into consideration when building a forecasting model for unemployment rates in several countries.

Directions for future research include: the extension of our analysis to explore predictability of the GUF at longer horizons, a further look to get a better understanding of the cross-country differences that we have reported here and a thorough analysis of the transmissions channels driving the international linkages in unemployment rates.

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Appendix

Appendix A. Descriptive Statistics.

Table A1: Descriptive statistics for the original series of monthly harmonized unemployment rate.

	Mean	Median	Mode	Std. Dev.	Var.	Min.	Max.	N° of obs.
Austria	4.9	4.9	5.7	0.66	0.44	3.6	6.3	229
Belgium	7.9	8.1	8.5	0.77	0.59	6	9.5	229
Canada	7.2	7.1	7	0.677	0.44	5.8	8.8	229
Czech Republic	6.8	7.1	7.2	1.4	1.95	3.4	9.3	229
Denmark	5.5	5.3	5	1.3	1.7	3.1	7.9	229
Finland	8.6	8.7	9	1.14	1.29	6.3	11.8	229
France	9.4	9.2	8.8	1.11	1.24	7.2	12.1	229
Germany	7.6	7.8	7.7	2.04	4.17	3.9	11.2	229
Hungary	7.8	7.4	5.7	1.99	3.98	4.3	11.4	229
Ireland	8	6.5	4.6	3.95	15.62	3.7	15.2	229
Italy	9.3	8.8	11.5	1.99	3.98	5.7	13	229
Japan	4.4	4.5	4.7	0.65	0.43	3	5.5	229
Korea	3.9	3.6	3.5	1.11	1.23	3	8.2	229
Luxembourg	4.4	4.7	2.4	1.4	1.95	1.8	6.6	229
Netherlands	5.1	5	5.7	1.24	1.54	3.1	7.9	229
Norway	3.5	3.4	3.4	0.64	0.4	2.3	5	229
Poland	12.4	10.3	9.6	4.64	21.51	5.3	20.5	229
Portugal	9.7	9	5.2	3.48	12.11	4.8	17.5	229
Slovak Republic	14.5	14	13.8	3.12	9.75	8.7	19.7	229
Slovenia	7.2	6.9	7.4	1.54	2.39	4.2	10.8	229
Spain	15.8	13.6	11.2	5.9	34.79	7.9	26.3	229
Sweden	7.2	7.2	7.8	0.96	0.92	4.9	9.3	229
UK	5.9	5.5	5.1	1.18	1.4	4.6	8.4	229
USA	6	5.5	5	1.76	3.08	3.8	10	229

Table A2: Descriptive statistics for measures of industrial production.

	Mean	Median	Mode	Std. Dev.	Variance	Min.	Max.	Obs.
IPI Austria	94.47	97.48	108.08	13.55	183.58	67.24	113.28	229
IPI Belgium	89.84	92.38	73.89	13.73	188.64	65.69	113.88	229
IPI Canada	107.31	108.86	N/A	5.36	28.71	93.12	114.92	229

IPI Czech Republic	93.85	95.65	106.38	16.85	283.99	61.58	124.53	229
IPI Denmark	108.38	109.09	113.39	7.11	50.57	92.79	122.19	229
IPI Finland	97.4	95.8	96.2	9.03	81.49	78	120.5	229
IPI France	107.24	110.29	111.33	6.52	42.49	94.04	117.07	229
IPI Germany	98.88	98.08	110.55	10.23	104.65	81.98	113.47	229
IPI Hungary	93.99	96.86	104.19	19.77	391.04	51.03	125.29	229
IPI Ireland	97.54	96.08	94.95	26.61	708.08	50.26	179.58	229
IPI Italy	106.64	112.33	118.66	10.57	111.67	90.43	122.38	229
IPI Japan	100.45	99.09	94.89	6.73	45.29	77.59	116.39	229
IPI Korea	80.52	81	53	23.95	573.59	34.1	113.8	229
IPI Luxembourg	100.03	98.71	101.41	10.28	105.72	69.92	121.71	229
IPI Netherlands	94.02	94.3	101.7	5.39	29.11	80.15	107.8	229
IPI Norway	107.56	110.22	112.71	8.97	80.52	87.4	123.38	229
IPI Poland	85.71	89.01	57.7	24.14	582.93	48.64	127.21	229
IPI Portugal	110.97	115.4	127.79	13.13	172.3	89.48	130.5	229
IPI Slovak Republic	89.16	90.04	59.59	27.74	769.68	49.91	142.94	229
IPI Slovenia	96.91	98.5	100.5	10.77	116.1	75	118.5	229
IPI Spain	107.97	110.27	99.36	11.82	139.76	89.04	129.05	229
IPI Sweden	100.37	99.41	97.41	6.83	46.63	88.21	117.31	229
IPI UK	108.66	112	113.3	5.85	34.24	97.7	117.2	229
IPI USA	97.41	97.1	91.68	5.34	28.53	86.66	106.66	229
LIBOR 1 Month	2.31	1.34	5.32	2.24	5	0.15	6.69	229

Appendix B. Correlation Coefficients

Table B1: Correlation Coefficients of the GUF and local monthly unemployment rates.

Countries	Correlation	Countries	Correlation
Austria	0.22	**Korea**	0.05
Belgium	0.19	**Luxembourg**	0.12
Canada	0.32	**Netherlands**	0.45
Czech Republic	0.44	**Norway**	0.21
Denmark	0.39	**Poland**	0.39
Finland	0.48	**Portugal**	0.30
France	0.53	**Slovak**	0.37

		Republic	
Germany	0.43	**Slovenia**	0.39
Hungary	0.36	**Spain**	0.49
Ireland	0.40	**Sweden**	0.20
Italy	0.18	**United Kingdom**	0.36

Source: Author´s elaboration