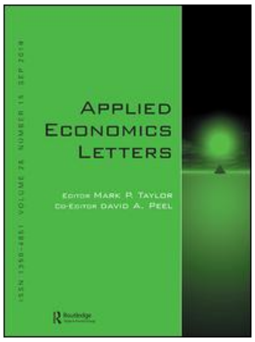

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Uncertainty and business cycle synchronization in Europe

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ABSTRACT
We assess empirically the role that uncertainty plays as a determinant of business cycle synchronization dynamics in the European Monetary Union. Using a time-varying measure of business cycle synchronization and Bayesian model averaging methods, we find that increase in uncertainty tends to robustly predict desynchronization, in particular for countries whose business cycles are not in line with those of the rest of the monetary union.

KEYWORDS
Business cycle synchronization; uncertainty; European monetary union; Bayesian model averaging

JEL CLASSIFICATIONS
F45; F44; C33

I. Introduction

Understanding the role of uncertainty as a determinant of macroeconomic dynamics has been a particularly important research topic in macroeconomics over the last years. Bloom (2014) presents a thorough summary of the work carried out in this topic up to 2014 and recent contributions such as those by Baker et al. (2016), Caldara et al. (2016) or Jo and Sekkel (2019) corroborate how central the role of measurement of uncertainty at the macroeconomic level has become in the modern academic literature. To the extent that uncertainty shocks exert effects in real variables, differences in the timing and intensity of uncertainty changes over time and across countries within a monetary union may have serious consequences for the synchronization of business cycles and affect the potential optimality of the single currency area. Multiple mechanisms link uncertainty dynamics to business cycle fluctuations (see Fernández-Villaverde and Guerró N-Quintana 2020, for a theoretical account of the macroeconomic effects of uncertainty), Precautionary savings due to an increase in uncertainty, for instance, affect aggregate demand and real interest rates, but effects can also appear on the supply side of the economy due to capital adjustment effects in firms. Since the quantitative relevance of these effects depend on institutional and structural characteristics of the economy, uncertainty shocks may lead to different macroeconomic reactions across countries and thus affect the degree of business cycle synchronization they experience.

In this paper, we assess empirically the effect of uncertainty dynamics on business cycle synchronization in the European Monetary Union (EMU), making use of the uncertainty measure recently developed by Baker et al. (2016) and time-varying measures of business cycle synchronization in the spirit of those presented in Crespo -Cuaresma and Fernández-Amador (2013a).[1] The index of uncertainty proposed by Baker et al. (2016) is based on frequency of the use of the word 'uncertainty' (or variants thereof) in country reports by the Economist Intelligence Unit. In order to ensure the robustness of our inference, we employ Bayesian model averaging techniques aimed at integrating away specification uncertainty. Our results indicate that differences in uncertainty dynamics across countries of EMU are robustly linked to the variation we observe in business cycle synchronization measures and that increases in uncertainty tend to widen business cycle differences. This is particularly the case in countries whose economic cycle is not harmonized with those of the rest of the economies in the currency

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[1]For a recent account of the econometric literature of optimum currency areas and business cycle synchronization, see Campos, Fidrmuc, and Korhonen (2019).

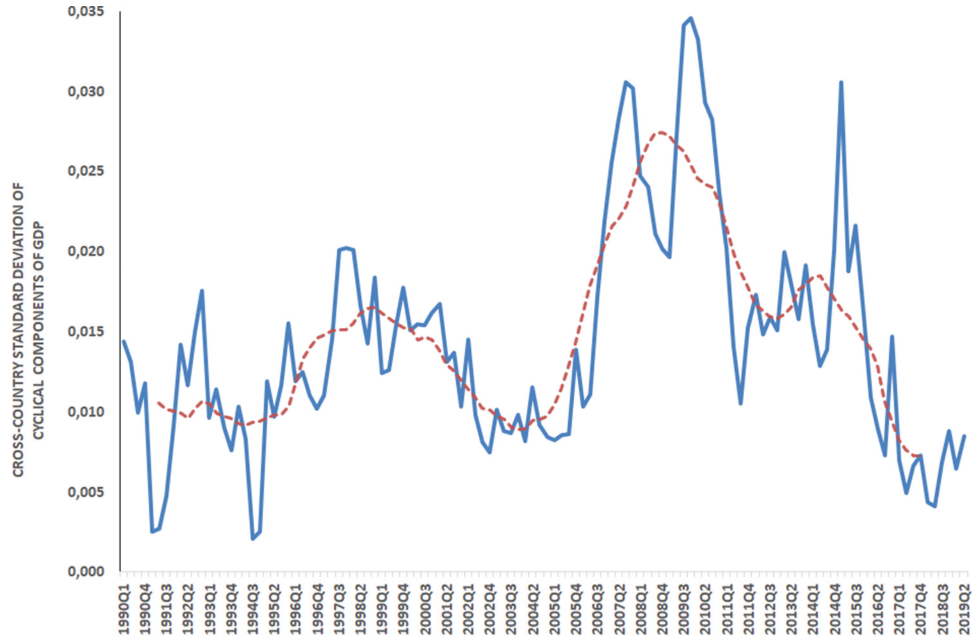

Figure 1. Business cycle synchronization in EMU: Cross-country standard deviation of HP-filtered GDP (1990Q1-2019Q2) and 3-year moving average.

area.

The paper is organized as follows. Section 2 presents results on the effects of uncertainty on business cycle synchronization in EMU for particular specifications. Section 3 shows the results of the model averaging exercise and section 4 concludes.

II. Assessing the link between uncertainty and business cycle synchronization

We aim at understanding the role of uncertainty (as measured by the uncertainty index developed by Baker et al., 2016) as a determinant of business cycle synchronization in EMU. Following Crespo - Cuaresma and Fernández-Amador (2013a) and Crespo -Cuaresma and Fernández-Amador (2013b), we construct country-specific time-varying measures of cyclical synchronization for country i by comparing the variation in business cycles at a given point in time t across EMU economies as compared to that of a counterfactual EMU excluding country i. Our measure of business cycle synchronization is therefore given by

$$\textbf{synch}_{it} = \log(s_{it}) - \log(s_t), \tag{2.1}$$

where $s_t = \sqrt{\left(\sum_j (c_{jt}) - \bar{c}_t)^2\right)/N}$ and $s_{it} = \sqrt{\left(\sum_{j\neq i}(c_{jt}) - \bar{c}_{jt})^2\right)/(N-1)}$ respectively denote the standard deviation of the estimates of the cyclical component of GDP (c_{it}) including all N countries that compose the monetary union and the same measure excluding country i. The indicator in equation (2.1) takes a negative value if excluding country i from the monetary union leads to a less heterogeneous group of countries in terms of values of the cyclical component of GDP, and can be interpreted as the percent change in cross-country variability of business cycles in a counterfactual EMU, which does not contain country i. If a monetary union that does not include country i at time t presents a higher degree of cyclical synchronization, $\textbf{synch}_{it}$ is negative, with lower (more negative) values of the variable implying a quantitatively larger level of asynchrony.

Employing estimates of the cyclical component of GDP applying the Hodrick Prescott filter to GDP data (sourced from Eurostat), the resulting cross-country standard deviation of cyclical components for EMU is presented in Figure 1 for the period 1990Q1-2019Q2. The synchronization figures are based on the particular composition of EMU in each particular moment. The most extreme episode of cyclical desynchronization took place around the time of the financial crisis, and a rebound of cross-country variation in business cycles occurred during the debt crisis in the euro area. The values of the desynchronization index at the end of our sample are among the lowest recorded in the period 1990–2019.

We start by entertaining panel regression models of the type

$$\mathbf{synch}_{it} = \beta \mathbf{uncert}_{it-1} + \gamma \mathbf{x}_{it-1} + \alpha_i + \lambda_t + \varepsilon_{it}, \tag{2.2}$$

where $\mathbf{uncert}_{it}$ is the level of uncertainty for country i at period t as measured using the index proposed by Baker et al. (2016), $\mathbf{x}_{it}$ is a vector of additional control variables, linked to changes in cyclical synchronization by the parameter vector γ, ε_{it} is an error term assumed to fulfil the standard assumptions of the linear regression model, α_i is a country fixed effect and λ_t is a year fixed effect. The measure of uncertainty is available from 1996Q1 and is obtained by recording the frequency of the use of the word 'uncertainty' (or variants thereof) in country reports by the Economist Intelligence Unit, with a higher figure implying a higher level of uncertainty (Ahir, Bloom, and Furceri 2018).[2]

Table 1 presents the estimation results of several specifications based on the model given by equation (2.2). In the first column, we show the results of a simple bivariate regression between our business cycle synchronization measure and the uncertainty variable, after controlling for country and time fixed effects. On average, increases in uncertainty tend to act as desynchronization shocks for countries within EMU, although the effect is only marginally significant. The effect is not qualitatively affected by the inclusion of the lagged synchronization measure as an additional control, in order to account for persistence in the dynamics of the business synchronization index (see column two in Table 1). A marginally significant negative effect of uncertainty on business cycle synchronization also exists after controlling for the volume of exports to other countries of the monetary union (in logs, sourced from the International Monetary Fund's *Direction of Trade Statistics*) and for the government balance as a percentage of GDP (sourced from Eurostat). The results of this model are presented in the third column of Table 1 and imply that the effects of uncertainty are present also after accounting for differences in the evolution of trade integration in the monetary union (which tends to lead to significant synchronization of business cycles) and in fiscal shocks (which are an important theoretical source of differences in business cycle synchronization patterns but in our regressions appear insignificant as a driver of synchronization differences over time). The negative effect captured by the uncertainty variable in these models is mostly driven by countries that experience desynchronization episodes, as can be seen in the results presented in the last column of Table 1. In this specification, we expand the specification by including the interaction between the uncertainty covariate and an indicator variable that takes value one if the synchronization variable is negative (that is, if in a given period the country's business cycle is relatively desynchronized with the rest of the EMU).

Table 1. Panel regression results: determinants of business cycle synchronization in EMU.

	(1)	(2)	(3)	(4)
Uncertainty	−0.0302 *	−0.0214 *	−0.0171 *	0.0331 *
	(0.0151)	(0.0103)	(0.00903)	(0.0159)
Lagged synchronization		0.532 ***	0.504 ***	0.419 ***
		(0.0234)	(0.0234)	(0.0167)
Exports to EMU			0.0291 **	0.0187 *
			(0.0123)	(0.00952)
Government balance			−0.0478	−0.0418
			(0.0856)	(0.0643)
Uncertainty × $I(\mathbf{synchro}_{it} < 0)$				−0.285 ***
				(0.0447)
N	1230	1215	1183	1183
R^2	0.024	0.304	0.299	0.413
adj. R^2	−0.046	0.254	0.245	0.368

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable is the synchronization measure in equation (2.1).
Country and time fixed effects in all specifications.

III. How robust is the link between business cycle synchronization and uncertainty?

The results presented in Table 1, based on individual specifications, point towards a negative effect of uncertainty episodes on business cycle synchronization within EMU countries, driven by the effect it has in economies which already present some

[2]The data on the uncertainty index are available for 15 out of the 19 countries that currently part of EMU, so the regressions do not include observations for Cyprus, Estonia, Malta and Luxembourg.

degree of desynchronization with the rest of the monetary union. We assess empirically the robustness of this result by obtaining estimates of the effect of interest that account for specification uncertainty using Bayesian Model Averaging (BMA) techniques (see for example Hoeting et al. 1999; Fernández, Ley, and Steel 2001b;a; Ley and Steel 2009, for some seminal contributions). We entertain models embedded in the specification given by

$$\mathbf{synch}_{it} = \sum_{j=1}^{4} \gamma_j \mathbf{synch}_{it-j} + \sum_{j=1}^{4} \beta_j \mathbf{uncert}_{it-j} + \sum_{k=1}^{N}\sum_{j=1}^{4} \theta_{kj} x_{kit-j} + \alpha_i + \lambda_t + \varepsilon_{it}, \quad (3.1)$$

where, in addition to the lagged dependent variable and the uncertainty variable, a pool of potential covariates $\{x_{kt}\}, k = 1, \ldots, N$ is used that contains lags of the trade and government balance variable, as well as the variable identifying negative values of $\mathbf{synch}_{it}$ ($I(\mathbf{synch}_{it} < 0)$ and interaction with the uncertainty, trade and government balance variables. For all variables, up four lags are allowed in the most general specification, leading to a total of 29 potential (non fixed effects) covariates. Assuming that the country and time fixed effects are always included in a model, the combination of those 29 variables lead to $2^{29} = 536,870,912$ possible specifications of the form given by equation (3.1). Constructing an estimate of the effect of a variable on business cycle synchronization (denoting this effect by ϕ) in the presence of model uncertainty implies evaluating the posterior distribution given by

$$P(\phi|y) = \sum_{f=1}^{M} P(\phi|y, M_f)P(M_f|y), \quad (3.2)$$

where $P(\phi|y, M_f)$ is the posterior distribution of ϕ conditional on specification M_f (of a total of $M = 2^{29}$ models) and $P(M_f|y)$ denotes the posterior probability of that particular model. The posterior model probability, in turn, can be written as the product of the marginal likelihood of the specification and its prior probability, $P(M_f|y) = P(y|M_f)P(M_f)$. The standard choice in BMA applications employs an improper non-informative prior for σ, the variance of the error term, $p(\sigma) \propto \sigma^{-1}$ and a prior over the slope coefficients in the the parameter vector β_k given by Zellner's g–prior (Zellner 1986). Zellner's g-prior uses a variance-covariance matrix of the full vector of parameters of the model which mimics the structure of the variance-covariance matrix of the ordinary least squares estimator but is scaled by the parameter g. This prior has the advantage of only requiring the elicitation of this parameter, for which several different values have been proposed in the literature (see, e.g. Foster and George 1994; Fernández, Ley, and Steel 2001b).[3] Prior model probabilities can be elicited by assuming a flat prior over all possible specifications, which implies that $p(M_f) = 2^{-M}$ for all f. Such a flat prior over models is however very informative on model size (see Ley and Steel 2009,, for example). A binomial-beta hyperprior on model size is proposed by Ley and Steel (2009) to overcome this problem. Such a binomial-beta prior on the inclusion of covariates in a given model leads to very flexible distributions for model size, including uninformative priors on the number of included covariates. Once the respective priors are elicited, posterior model probabilities can be computed and inference in the presence of model uncertainty can be efficiently carried out employing Markov Chain Monte Carlo Model Composition (MC^3) methods (Madigan and York 1995) in order to approximate the relevant posterior distributions.

We start by applying BMA to the full set of specifications assuming that the country and time fixed effects are included in all of them, and in a second step, we treat them as potential variables that may or may not be included in a given model. Since our specifications also contain models with interaction terms, it might be argued that the prior over models should include a down weighting of specifications that contain the interaction variable without the parent variables that create the interaction as additional controls (see Chipman 1996; Crespo -Cuaresma 2011; Papageorgiou 2011; Moser and Hofmarcher 2014). The third BMA

[3]Approaches based on hyperprior specifications for g have also been put forward by Liang et al. (2008); Feldkircher and Zeugner (2009); Ley and Steel (2012).

setting we entertain combines the standard BMA framework of the normal linear model with a strong heredity prior that assigns a prior model probability of zero to specifications where the interaction term is present, but one of the parent variables is missing. Such a setting leads to a smaller prior probability of models including interactions, and thus to more evidence from the data being necessary to achieve robustness for interacted variables.

In Table 2, we present the main results of the BMA exercise, based on five million Markov Chain steps in the model space after 10,000 burn-ins. We present the posterior inclusion probability of each variable (the posterior model probability of specifications including that particular covariate), which is routinely used as a measure of robustness as an explanatory factor of the phenomenon under scrutiny, as well as the mean and standard deviation of the posterior distribution of the effect. In all cases, we use a binomial-beta prior for covariate inclusion implying a flat prior over model size (Ley and Steel 2009) and a BRIC prior over the parameters of a given specification (Fernández, Ley, and Steel 2001a).

Across all of our BMA settings, the results concerning nature of the determinants of business cycle synchronization in EMU paint a similar picture concerning the variables whose effects are considered to be robust to specification uncertainty. Very few variables achieve large posterior inclusion probabilities beyond lags of the dependent variable, which appear necessary to account for the persistence in the business cycle synchronization variable. The uncertainty variable is an extremely robust variable in desynchronization regimes, as measured by the posterior inclusion probability and the precision of its estimate. The effect implies that in the course of episodes of business cycle desynchronization, increases in uncertainty tend to systematically lead to further desynchronization and thus lead to a more unstable monetary union in the sense of optimum currency area criteria. The effect implies that an increase in one standard deviation of the uncertainty variable in countries which are in

Table 2. Bayesian model averaging results.

	(1) Fixed country and time effects			(2) Standard BMA			(3) Strong heredity		
Variable	PIP	Post. Mean	Post. SD	PIP	Post. Mean	Post. SD	PIP	Post. Mean	Post. SD
synch_{t-1}	**1.000**	**0.334**	**0.028**	**1.000**	**0.364**	**0.028**	**1.000**	**0.363**	**0.028**
synch_{t-2}	0.003	0.000	0.002	0.001	0.000	0.001	0.001	0.000	0.001
synch_{t-3}	**0.999**	**0.175**	**0.031**	**0.999**	**0.193**	**0.029**	**0.999**	**0.192**	**0.029**
synch_{t-4}	0.111	0.009	0.028	0.050	0.005	0.021	0.057	0.005	0.022
uncert_{t-1}	0.003	0.000	0.001	0.001	0.000	0.000	**0.976**	**0.003**	**0.012**
uncert_{t-2}	0.003	0.000	0.001	0.001	0.000	0.001	0.001	0.000	0.001
uncert_{t-3}	0.003	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000
uncert_{t-4}	0.003	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000
$\mathrm{Exports}_{t-1}$	0.012	0.000	0.007	0.001	0.000	0.000	0.001	0.000	0.000
$\mathrm{Exports}_{t-2}$	0.017	0.001	0.007	0.001	0.000	0.000	0.001	0.000	0.000
$\mathrm{Exports}_{t-3}$	0.019	0.001	0.005	0.001	0.000	0.000	0.001	0.000	0.000
$\mathrm{Exports}_{t-4}$	0.018	0.000	0.004	0.001	0.000	0.000	0.001	0.000	0.000
$\mathrm{Gov.Bal.}_{t-1}$	0.003	0.000	0.003	0.001	0.000	0.001	0.001	0.000	0.001
$\mathrm{Gov.Bal.}_{t-2}$	0.003	0.000	0.003	0.001	0.000	0.002	0.001	0.000	0.001
$\mathrm{Gov.Bal.}_{t-3}$	0.003	0.000	0.003	0.001	0.000	0.002	0.001	0.000	0.001
$\mathrm{Gov.Bal.}_{t-4}$	0.002	0.000	0.003	0.001	0.000	0.002	0.001	0.000	0.002
$I(\mathrm{synch}_{it} < 0)$	**0.973**	**−0.128**	**0.078**	**0.854**	−0.037	**0.020**	**1.000**	**−0.042**	**0.007**
$I(\mathrm{synch}_{it} < 0) \times \mathrm{uncert}_{t-1}$	**1.000**	−0.162	**0.027**	**1.000**	−0.163	**0.026**	**0.986**	**−0.162**	**0.034**
$I(\mathrm{synch}_{it} < 0) \times \mathrm{uncert}_{t-2}$	0.020	0.001	0.009	0.007	0.000	0.005	0.000	0.000	0.000
$I(\mathrm{synch}_{it} < 0) \times \mathrm{uncert}_{t-3}$	0.003	0.000	0.002	0.001	0.000	0.001	0.000	0.000	0.000
$I(\mathrm{synch}_{it} < 0) \times \mathrm{uncert}_{t-4}$	0.002	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.000
$I(\mathrm{synch}_{it} < 0) \times \mathrm{Gov.Bal.}_{t-1}$	0.003	0.000	0.006	0.001	0.000	0.003	0.000	0.000	0.000
$I(\mathrm{synch}_{it} < 0) \times \mathrm{Gov.Bal.}_{t-2}$	0.004	0.000	0.008	0.001	0.000	0.005	0.000	0.000	0.000
$I(\mathrm{synch}_{it} < 0) \times \mathrm{Gov.Bal.}_{t-3}$	0.004	0.000	0.007	0.001	0.000	0.004	0.000	0.000	0.000
$I(\mathrm{synch}_{it} < 0) \times \mathrm{Gov.Bal.}_{t-4}$	0.008	0.001	0.012	0.002	0.000	0.007	0.000	0.000	0.001
$I(\mathrm{synch}_{it} < 0) \times \mathrm{Exports}_{t-1}$	0.143	0.001	0.009	0.049	0.000	0.002	0.000	0.000	0.000
$I(\mathrm{synch}_{it} < 0) \times \mathrm{Exports}_{t-2}$	0.157	0.002	0.010	0.040	0.000	0.002	0.000	0.000	0.000
$I(\mathrm{synch}_{it} < 0) \times \mathrm{Exports}_{t-3}$	0.161	0.003	0.020	0.034	0.000	0.004	0.000	0.000	0.000
$I(\mathrm{synch}_{it} < 0) \times \mathrm{Exports}_{t-4}$	0.136	0.001	0.017	0.042	0.000	0.003	0.000	0.000	0.000

PIP stands for 'Posterior inclusion probability'. Results based on 10,000,000 MCMC steps after a burn-in phase of 10,000 steps.
Strong heredity prior in setting 3 based on Crespo -Cuaresma (2011).

a desynchronization phase translates on average to a reduction of 0.184 standard deviations in the business cycle synchronization variable.

IV. Conclusions

Business cycle synchronization is known to play a central role as a determinant of the optimality of currency areas since the seminal contribution by Mundell (1961). In this contribution, we show that uncertainty plays a central role in explaining differences in the synchronization stage of the business cycle of economies within EMU and belongs to the most robust determinants of changes in cyclical synchronization for European economies. The effect is particularly important for countries whose business cycle in desynchronized with the rest of the monetary union. The results of the paper and the availability of novel measurements indicate that monitoring the dynamics of uncertainty should be an important component of the assessment of sustainability of monetary unions.

The strong increase in uncertainty associated with the COVID pandemic (see Baker et al. 2020, for example) provides an interesting laboratory to further assess the robustness of the relationship found in this study. Exploiting the differential dynamics of uncertainty across European economies during the pandemic is expected to help us to understand emerging business cycle synchronization patterns in the continent over the coming years.

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