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ABSTRACT

The failure to predict the Great Recession. The failure of academic economics? A view focusing on the role of credit*

Much has been written about why economists failed to predict the latest financial and real crisis. Reading the recent literature, it seems that the crisis was so obvious that economists must have been blind when looking at data not to see it coming. In this paper, we illustrate this failure by looking at one of the most cited and relevant variables in this analysis, the now infamous credit to GDP chart. We compare the conclusions reached in the literature after the crisis with the results that could have been drawn from an ex ante analysis. We show that, even though credit affects the business cycle in both the expansion and the recession phases, this effect is almost negligible and impossible to exploit from a policymaker's point of view.

JEL Classification: C22 and E32
Keywords: business cycles, credit, financial crisis and forecasting

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1 Introduction

Much has been written about why economists failed to predict the latest financial and real crisis. From the press through specialized blogs to academic papers, everybody has highlighted the failure of the profession to foresee this crisis. As is well known, even the Queen of England, when visiting the London School of Economics in November 2008, asked why no one saw the credit crunch coming[1]. At the same time, Paul Krugman, in the New York Times[2], bemoans the profession is blindness to the possibility of catastrophic failures in a market economy. Finally, a recent report, Colander et al (2009), written by scholars and quoted by numerous bloggers, claims that it has been a misallocation of research efforts in economics, and, in particular, an insistence on constructing models that disregard the key elements driving outcomes in the real-world markets that have been the main cause of the inability of the economics profession to predict the current recession.

The recent downturn has also highlighted the lack of consensus in macroeconomic thinking about how far the financial system influences economic activity. Basic economic theory suggests that, in a frictionless world, the shocks originating in credit markets play only a minor role in explaining business cycles. However, the presence of financial imperfections can amplify their effect on the real economy and, thus, disturbances in credit markets can lead to larger cyclical fluctuations in the real economy. These frictions also provide micro-fundamentals for analyzing the channels of transmission. Bernanke and Gertler (1989, 1995); Bernanke et al. (1999); and Kocherlakota (2000) are some of the earlier papers that model the different channels of transmission between the financial sector and the real economy. However, as Krugman points out in his previously quoted article in the New York Times, ”at the beginning of the recession, the impact of dysfunctional finance, had not been at the core even of Keynesian economics”. In fact, the most influential dynamic general equilibrium models developed just before the recession by Chistiano et al. (2005) and Smets and Wouter (2007) do not incorporate any financial accelerator mechanism. The debate at that time was about the effect of frictions, nominal and real, and the role of monetary policy to offset these effects on output and inflation. Although the financial accelerator mechanisms had been explored in

[1] Daily Telegraph, November 28th 2008

[2] Paul Krugman, New York Times Magazine, September 2nd 2009.

the literature, other features of the data seemed more promising to explain business cycle fluctuations, all the more so since these fluctuations were dramatically reduced during the quiet times of the Great Moderation.

However, with the financial crisis, a newly flourishing literature has rekindled interest in the topic of credit and business cycles. A broad and basically empirical body of literature, has looked back at history and focused on documenting the timing of financial crises, establishing their typology and detecting the differences between emerging and advanced economies. Reinhart and Rogoff (2009) build a massive database that encompasses the entire world across eight centuries, and Laeven and Valencia (2008, 2010) provide data on the starting dates and characteristics of systemic banking crises over the period 1970-2009, as well as a broad coverage of crisis management policies. Both papers conclude that there are strong similarities between recent and past crises and, consequently, the Great Recession is nothing new.

In the wake of this work, and maintaining an empirical approach, another group of studies attempts to explore the relationship between financial and macroeconomic variables in greater depth. Following the seminal work of Kaminsky and Reinhart (1999), these papers pay special attention to the behavior of certain key variables in the crisis environment, the similarities between the financial and the real cycles and the ability of financial variables such as credit to predict recessions. Schularick and Taylor (2009) construct a new historical database for 14 countries over 140 years and show that credit growth is a powerful predictor of financial crises, suggesting that policymakers should pay more attention to credit. The same database has been used by Jorda et al. (2011a, b) with different goals. Jorda et al. (2001b) replicate the results of Schularick and Taylor (2009) and introduce external imbalances, concluding that credit growth emerges as the single best predictor of financial crises, and Jorda et al. (2011a) detect the turning points and look at the behavior of real and financial aggregates across business cycle episodes. Their results highlight that credit booms tend to be followed by deeper recessions and sluggish recoveries.

Among other authors who use a similar methodological approach, we can mention Gourinchas and Obsfeld (2011), Mendoza and Terrones (2008) and Claessens et al. (2011b, c). Gourinchas and Obsfeld (2011) classify financial crises into different types by using several historical databases and analyze how key economic variables behave in the different categories of crises, estimating a logit panel to assess their ability to predict crises. Mendoza and Terrones (2008) identify credit booms with threshold values and analyze the performance of some macroeconomic and financial variables around their peaks. Claessens et al. (2011a, b) provide a comprehensive and quantitative characterization of financial crises by using a repeatable algorithm, instead of resorting to historical records, and conclude that they tend to be long, severe and highly synchronized. The link between financial and business cycles is addressed by Claessens et al.(2011c), who find that the duration and amplitude of recessions and recoveries tend to be influenced by the strength and intensity of financial crises. Finally, the International Monetary Fund (2009) presents a compendium of most of these results[3].

All these papers have much in common, both in the stylized facts derived from them and in their methodological foundations. They provide considerable evidence that financial markets, and credit in particular, play an important role in shaping the economic cycle, in the probability of financial crises, in the intensity of recessions and in the pace of recoveries. The argument is that the strong growth of domestic credit and leverage that fuelled the expansion phase became the trigger for a financial crisis and, therefore, for a recession[4]. A common finding is that downturns associated with financial crashes are deeper and their recoveries slower.

At this point, with the clarity and the robustness of previous results, it seems surprising that the financial accelerator mechanism did not appear earlier on the agenda of the theoretical business cycle models. It seems that the link between financial and real crises is so obvious that economists should have been blind when looking at data before the crisis to miss such an important feature of the data. Significantly, however, all the papers that find this clear empirical evidence date from after the financial crisis started. The question to ask now is whether this ex post evidence, could be obtained ex-ante and if it is sufficiently robust to assist with economic policy decisions.

From an econometric point of view, these papers employ a similar methodology. Most of them consider that financial crises or recessions are known a priori,

[3] As a result of these empirical findings a growing literature is now seeking how to include richer financial sectors into dynamic stochastic general equilibrium (DSGE) models (see, among others, Christiano et al. 2010; Gertler and Kiyotaki, 2011).

[4] Reinhart and Reinhart (2011) stress that this argument is especially important for the decade of prosperity prior to the fall of 2008.

either by using historical records or by pinpointing them with non-parametric techniques. Crises are usually treated as isolated events, exogenous to the model, and the behavior of some financial and macroeconomic variables is analyzed only near to the turning points. Therefore, this research does not take into account the fact that recession dating is uncertain in real time. Furthermore, when the macroeconomic variables have the property of accumulating during the expansions periods, a potential bias may arise because these variables usually present high levels just before the turning points. For example, from this literature, an analyst could extract the lesson ”Credit to GDP growth is a particularly reliable indicator of recession when the experiences of both advanced and emerging economies are considered together[5]”. However, during long periods of expansions, credit to GDP growth is high and there is no recession. Also, credit as a proportion of GDP accumulates over time endogenously in different theoretical models, as in Gertler and Karadi (2011), Gertler and Kiyotaki (2010) and Christiano et al. (2010), and, therefore, it is endogenously high when expansions are long. Yet these high levels before turning points do not imply any power of the credit to GDP ratio in predicting the turning points. In medical terminology, the previous literature is more interested in the ”anatomy” of financial crises, after they have occurred, than in ”clinical medicine”, that is, diagnosis from the symptoms. But both perspectives are necessary to practice good medicine. Therefore, although these former papers have made a valuable contribution to our understanding of the complex relationships between the real and the financial cycles, we need to take a step further. For the lessons extracted from the data to be of value to policymakers in their day-to-day policy decisions, we have to understand the dynamics of these financial variables in real time without forgetting the uncertainty about turning points.

The key point of our proposal is to consider the cyclical phases and, especially, recessions in an environment of uncertainty. Policymakers that see credit to GDP growing have to decide when the growth is dangerously high and could generate a turning point. If a long expansion keeps generating a high credit to GDP ratio endogenously, to cut credit dramatically could unnecessarily shorten the period of healthy growth. Therefore, the key question for a policymaker is to what extent the level of credit to GDP (or its variation) observed in period ”t” increases or

[5] Viñals (2012) quoting Global Financial Stability Report, IMF, September 2011

not the probability of being in a recession in "$t+1$", or whether it changes the characteristics of future cyclical phases.

These are the questions that we try to answer in this paper. In order to do so, we propose a novel and robust technique for dating and characterizing business cycles and for analyzing the effect of financial and other types of variables. We combine temporal and spatial data and we show that this approach is legitimate, notably reduces the uncertainty associated with the estimation of recession phases and improves forecasting ability in real time.

Our results can be summarized as follows. Credit build-up exerts a significant and negative influence on economic growth, both in expansion and recession, increasing the probability of remaining in recession and reducing that of continuing in expansion. However, these effects, although significant, are almost negligible on the business cycle characteristics. We show that there is no significant gain in forecast performance as a consequence of introducing credit. Therefore, in contrast to the previous literature, our findings indicate that the role of credit in the identification of the economic cycle and its characteristics is very limited.

Our results also explain why financial accelerator mechanisms have not played a central role in the models that describe business fluctuations. The financial accelerator was not a key point in explaining business fluctuations simply because, empirically, it did not have such a close relationship to the business cycle, either in a sample (prior to the crisis) or in an out of sample approach, once the uncertainty in dating recession periods is included in the model.

The rest of the paper is structured as follows. Section 2 presents the results of the previous literature. Section 3 describes the country model estimation, the different steps for building the global model, and it appraises the forecast performance of the global model with and without credit. Finally, Section 4 concludes.

2 Credit and the business cycle. Explaining the past

Suppose that a policymaker has to decide whether to dramatically cut credit growth in an economy or to let it continue to grow. Assuming that this policymaker likes to make informed decisions, he/she will read the literature on the relation between credit and growth and will probably reach the conclusion that credit to GDP growth is a particularly reliable indicator of recessions. As we mentioned before, this conclusion derives from the literature that supports the influence of financial variables on the economic cycle. All these papers reach the same conclusion but using different transformations of the credit to GDP ratio, levels, variations or variations divided by expansion durations. For example, Gourinchas and Obsfeld (2011) and Kamisnky and Reinhart (1999), use the series in levels. Figure 1.a plots this series in levels for the US. As can be appreciated in the figure, it is a variable that increases during expansion periods, as is predicted by the models that consider that credit grows endogenously during booms. Another way to show, more formally, the intuition that emerges from Figure 1.a can be derived from running the following regression:

$$y_t = \alpha + \beta * t + \varepsilon_t \tag{1}$$

where y_t is the credit to GDP ratio only in expansion periods, and t is a variable that has a trend during each expansion period (using NBER dating) which starts from 1 at the beginning of every new period. As shown in Table 1, the estimated β coefficient for the US case is positive and significant, confirming what can be seen in the figure. This is not only a characteristic of the US series from 1950.1 to 2011.2. We repeat this exercise with data for 39 OECD countries, using Bry and Boschan (1971)'s algorithm to date expansions and recessions, and the results are even clearer. The credit to GDP ratio has a significant trend during expansion periods because the β coefficient is also positive and significant. Finally, the results are the same when using the annual sample of Jorda et al. (2011a, b) from 1850 to 2008. Therefore, we can affirm that the credit to GDP ratio has a positive and significant trend during times of expansion.

Trying to avoid this trending behavior, some other papers use the variation in GDP (IMF 2009; Jorda et al. 2011b). However, as shown in Figure 1.b, this variable still has a trend in the US. To test for this trending behavior, we do the same as we did before with the ratio but, instead of the ratio, we use the variation in the ratio. The results, for the US case, the 39 countries case and the Jorda et al. (2011a, b) case are displayed in the second panel of Table 1. As can be seen, the β coefficient is also positive and significant, showing that there is still a trend in this variable. This is a standard result when one variable (credit) grows faster during times of expansion times than the other (GDP), which seems to be a stylized fact in the data.

Finally, some other papers construct different transformations of this ratio, the most popular being credit intensity (Jorda et al. 2011b). This variable is defined as the cumulative difference between credit growth and GDP growth normalized by the duration of the expansion. It is plotted in Figure 1.c for the US. As in the two previous cases, this variable has a significant trend. This trending behavior is corroborated, as in the two previous cases, by carrying out the same regression analysis, but with y_t representing credit intensity. The results are shown in the third panel of Table 1. Credit intensity still presents a positive and significant expansion-related trend. We will now analyze the implications of the expansion-related trending behavior of the credit to GDP ratio (or its variations) on the standard econometric approach used in the literature.

TABLE 1
REGRESSION ON TRENDING EXPANSIONS

	β	t_ratio
	US DATA	
ratio	0.0010	3.8428
variation in ratio	0.0087	2.6282
credit intensity	0.0147	2.2028
	OECD 39 COUNTRIES	
ratio	0.0530	17.0298
variation in ratio	0.0224	8.9129
credit intensity	0.0210	5.1895
	JORDA ET AL. (2011)'S DATA	
ratio	0.0030	6.2066
variation in ratio	0.0259	4.1160
credit intensity	0.0444	3.0135

Notes: We have estimated the regression $y_t = \alpha + \beta * t + \varepsilon_t$ where y_t is the credit to GDP ratio only in expansion periods, and t is a variable that has a trend during each expansion period. In the cases of OECD data and Jorda et al. (2011)'s data, we have used the global model.

All the papers that find a link between credit and the business cycle consider crises, both their location and their typology, as exogenous variables. The econometric methodology used in Gourinchas and Obstfeld (2011); Jorda et al. (2011a) and Schularick and Taylor (2009) applies a panel logit model where the left-hand side variable is a dummy that takes the value 1 several periods before the crisis and is clearly explained by a set of macroeconomic variables, among which credit stands out. In order to illustrate the econometric problems associated with this approach, we construct a variable that mimics the trending path of credit as follows. First, we generate a variable with 0s and 1s following a random Markov chain with constant transition probabilities using the 0.9 and 0.7 parameters for the transition probabilities as estimated in Hamilton (1989). In this way, we generate a sequence of ”artificial recessions” completely impossible to forecast by definition (it is driven by a random process with constant transition probabilities). In addition, we construct a counter that accumulates during the expansion phase and decays linearly during the recession phase until it returns to 1 at the beginning of the following expansion, and we take logs of this accumulator to provide a shape similar to the data in Figure 1.a[6]. We call this variable ”$cumul_t$” (See Figure 1.d). Finally, for the artificial recession periods, we generate, in the spirit of Gourinchas and Obsfeld (2011), a variable ”z_t” which takes the value 1 if an artificial crisis occurs between periods $t+1$ and $t+3$, and 0 otherwise. As they do, we estimate a logit model relating ”z_t” and ”$cumul_t$”. We repeat this exercise 1000 times for a series of 5000 observations. We find that the variable ”$cumul_t$” is significant at 5% in 83% of the cases. The intuition of the result is clear. Even though, by construction, ”$cumul_t$” does not have any predictive power on recessions, it is usually high at the end of expansion periods. Therefore, spuriously, there is a significant ”predicting” behavior at the end of the expansion, although, by construction, the number of periods in which the economy is in artificial expansion” has no predictive power on the end of the expansion.

Therefore, the apparent influence of credit could be due just to the build-up behavior and we can get the same result with a random variable that contains no more information about the business cycle than that derived from the accumulation behavior which reproduces the typical ”boom and bust” of economic fluctuations. This result shows that we can only obtain descriptive conclusions about the behavior of credit without any possibility of obtaining inferences about future turning points. However, the lesson that policymakers seem to obtain from this literature is very policy-oriented: ”Credit to GDP growth is a particularly reliable indicator of recession”. As a result, policymakers could feel that they have to cut credit dramatically when it is high in order to prevent a not-forthcoming recession, but with this decision they could shorten a healthy future expansion period.

[6]The results do not depend on the transformation of the accumulator. We use logs just to give a nice shape that coincides with the shape of the credit to GDP ratio of Figure 1.a

In addition to the previous problem associated with the trending behavior of the credit to GDP ratio, another econometric issue in the previous literature needs some further comments. As we mentioned, in this literature, crises, both their location and their typology, are treated as exogenous variables. However, in the definition of turning points, credit is one of the variables which is considered. A fall in credit in period "$t, t+1 \ldots t+k$" contributes to the definition of a turning point in period "t". Given that the credit to GDP ratio and its variations ("$credit_t$") is a variable that presents persistence, if we define the variable "future recession in the next k periods" as before, "z_t" and we run the regression:

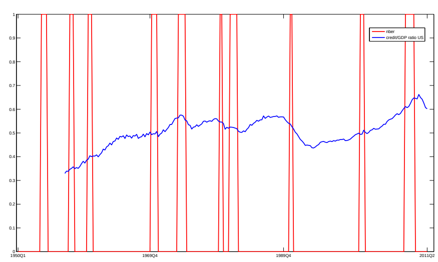
$$z_t = \alpha + \beta * credit + \varepsilon_t \tag{2}$$

$E(\varepsilon_t, credit_t) \neq 0$, because "$z_t$" is defined looking at the evolution of "$credit_{t+1 \ldots t+k}$" and, given that $credit_t$ presents autocorrelation, $E(\varepsilon_t, credit_t) \neq 0$ and, therefore, β is upwardly-biased and no conclusions can be drawn from its estimation.

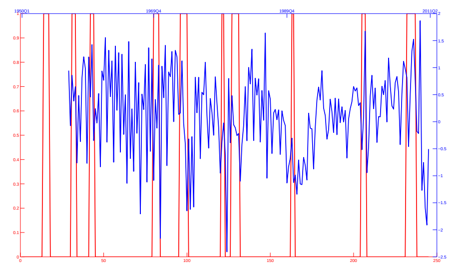
Finally, one basic accounting exercise should be considered when analyzing financial and real crises. Even though financial and real crises are different events, they dramatically coincided in the latest recession. The fact that the Great Recession was preceded by a build-up of domestic credit in most developed countries could somehow bias our views about the relation between financial and real crises[7]. In order to illustrate this point, we identify, for the sample of 39 OECD countries, between 1950.1 and 2011.2, using the Bry-Boschan (1971) algorithm, 149 recession periods. Of these, only 45 coincide with one of the financial crises documented by Gourinchas and Obstfeld (2011), and 31 of the 45 correspond to the recent crisis. The others are mostly currency crises. Furthermore, for the sample that we have, Gourinchas and Obstfeld (2011) identify 143 financial crises, of which only 45 correspond to a real crisis. Eliminating the last 31 recent crises, during the period 1950.1 to 2011.2, for a sample of 39 countries, of the 230 financial or real crises (143-31 financial, 149-31 real), we find that only 14 cases (6%) are both financial and real. With this evidence in mind, it seems that to exploit the relation between financial and real variables with the purpose of forecasting or preventing future recession periods is definitively a long shot.

[7] Jorda et al. (2011a) make the point that excess credit is a problem in all business cycles not just in financial crises.

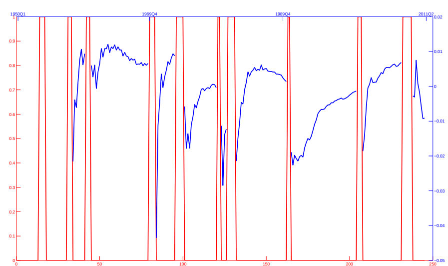
And this is our final goal. We want to provide policymakers with the appropriate tools to make optimal policy decisions about allowing credit to grow or not. In order to do that, we are going to analyze the forecasting power of the level of credit to GDP (or its variation) observable in period "t", on both, the probability of being in a recession in "$t+1$" and the characteristics of this future recession period. We are going to focus on inferring the future with the current information. But first, we need a formal definition of turning point and a description of the characteristics of the cycle.



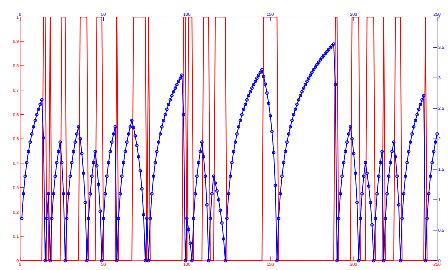
(a) Credit to GDP ratio



(b) Credit ratio variations



(c) Credit intensity



(d) Artificial variable with build-up behavior

FIGURE 1. Trending expansion behavior of credit

3 Credit and the business cycle. Inferring the future

We use GDP as the reference variable to analyze the business cycle. Our source is the OECD database but we check for coincidence with national sources. Our sample of reference is 1950.1 to 2011.2 for 39 OECD countries. Appendix 1 shows the details of the countries, their acronym, the sample size of each series, the analysis of the structural breaks and the level of coincidence between national and OECD sources. Due to clear methodological changes in the data or samples that are too short, we have had to discard six countries. Figure A1 (Appendix 1) plots the GDP series for the 33 countries.

3.1 Dating turning points

Having defined the series of reference, we identify turning points with the non-parametric framework of Bry and Boschan (1971) (BB). As is well known, this algorithm provides a formal content to the graphical analysis of Burns and Mitchel (1946). Although initially designed for monthly data, BB can be easily adapted for quarterly data [8]. We have considered a minimum cycle and phase length criterion, restricting business cycles and phases to last at least 5 and 2 quarters, respectively. The outcome of applying the BB procedure is displayed in Figure A1 (Appendix 1) for the thirty-three countries of our panel. Once the turning points have been located, and following Harding and Pagan (2002), we dissect the business cycle and calculate some outcomes such as the frequency of recessions, measured as the number of months in recession over the total, and the mean duration, amplitude, cumulation and excess of recessions and expansions. The frequency of recessions is 0.14 on average, the mean duration of the recessions is 4.23 quarters and the mean duration of the expansions 24.4 quarters. These results are plausible and agree with the stylized fact that expansion periods are longer than recessions and are in line with the durations estimated by the NBER for the US and the IMF (2009) for a wide sample of advanced countries

[8] Our dating algorithm is based on Bry and Boschan (1971) and is an adaptation of Watson (1994).We have also tried with the BBQ code of Harding and Pagan (2002) and obtain similar results.

3.2 Inferring the future without credit

3.2.1 Country model estimation

Even though the BB algorithm is a very popular method to date business cycle, it has the inconvenience that it is mainly a descriptive method. Inferences can not be made about future recession periods. The most popular alternative method that allows us to date the cycle and to make inferences about future periods is the Markov switching (MS) approach proposed by Hamilton (1989). The MS models characterize the evolution of a variable through a process of conditioned mean to a state of a specific nature. The changes in value in this dynamic process will allow us to differentiate periods of expansion and contraction. Regime shifts are governed by a stochastic and unobservable variable which follows a Markov chain. In general, we consider the following process for the log growth of GDP[9]:

$$dy_{tc} = \mu_{S_{jc}} + \varepsilon_{tc} \tag{3}$$

where dy_{tc} is the growth rate of GDP in country c, $\mu_{S_{jc}}$ is the vector of Markov switching intercepts and $\varepsilon_{tc}/_{S_{jc}}$ ~N(0, σ). To complete the statistical specification, it is standard to assume that these varying parameters depend on an unobservable state variable S_{j_c} that evolves according to an irreducible m-state Markov process where p_{ij} controls the probability of a switch from state j to state i.

We have estimated a MS model with 2 states ($i,j = 1,2$) and a constant variance for each country:

$$\begin{aligned} dy_{tc} &= \mu_{1c} + \varepsilon_{tc} \text{ for state 1} \\ dy_{tc} &= \mu_{2c} + \varepsilon_{tc} \text{ for state 2} \end{aligned} \tag{4}$$

Assuming a classical cycle, μ_1 and μ_2 are associated with expansion and recession phases, respectively, and $p_{11} = p$ and $p_{22} = q$ represent the probability of being in expansion/recession and staying in the same state.

The results of the estimation of MS models with a MLE algorithm are displayed in Table 2. We observe that μ_1 and μ_2 take average values of 1.16 and -1.87, respectively. The mean probability of expansion and recession is 0.96 and 0.66, re-

[9]MS estimation requires stationarity. The application of a battery of unit root tests confirms the result that GDP series are I(1) in log levels.

spectively. However, and as happened in the BB case, the results show a significant heterogeneity. Furthermore, the standard errors associated with the probability of recession are usually high, which results in a great uncertainty about the duration of recessions. In some cases, BG, FR, GR, IT, JP and PT, we obtain surprising values. For instance, in the case of France, we find a growth cycle instead of a classical cycle. This is the consequence of two different trends in the evolution of the growth rate[10]. Therefore, even though the MS model seems an appropriate tool to define recession periods, there is a certain degree of uncertainty about the parameter estimates when the sample is short and, consequently, there are few cycles. To incorporate credit into this type of system and to test the significance of the estimated credit parameters always leads to accepting the null of non-significance because of the low power of the test. For an accurate test, we will need a longer sample or to incorporate Bayesian priors. This is the purpose of the following section.

TABLE 2

MS MODEL ESTIMATION

	μ_1	μ_2	σ^2	p	q		μ_1	μ_2	σ^2	p	q
AG	1.84 (0.21)	−1.41 (0.40)	1.69 (0.33)	0.95 (0.02)	0.84 (0.08)	IS	1.30 (0.15)	−0.19 (0.27)	0.62 (0.15)	0.94 (0.03)	0.77 (0.13)
AU	0.95 (0.08)	−0.33 (0.60)	1.12 (0.13)	0.98 (0.01)	0.60 (0.25)	IT	1.64 (0.13)	0.28 (0.07	0.59 (0.07)	0.87 (0.05)	0.95 (0.01)
BD	0.70 (0.06)	−2.96 (0.26)	1.00 (0.11)	0.98 (0.00)	0.23 (0.23)	JP	2.26 (0.02)	0.57 (0.09	1.24 (0.13)	0.99 (0.00)	0.99 (0.00)
BG	1.17 (0.07)	0.33 (0.06)	0.24 (0.03)	0.91 (0.03)	0.94 (0.02)	LX	1.20 (0.24)	−2.26 (0.07)	2.69 (0.63)	0.95 (0.02)	0.46 (0.31)
BR	1.02 (0.18)	−3.31 (0.79)	2.03 (0.40)	0.94 (0.02)	0.29 (0.24)	MX	1.08 (0.07)	−5.90 (0.61)	1.08 (0.11)	0.99 (0.01)	0.33 (0.27)
CL	1.57 (0.14)	−1.11 (0.62)	1.55 (0.27)	0.96 (0.01)	0.55 (0.21)	NL	0.69 (0.08)	−2.43 (0.50)	0.75 (0.11)	0.96 (0.01)	0.19 (0.23)
CN	0.97 (0.06)	−0.50 (0.31)	0.56 (0.06)	0.98 (0.00)	0.79 (0.10)	OE	0.78 (0.06)	−2.07 (0.52)	0.79 (0.08)	0.99 (0.00)	0.43 (0.26)
CZ	0.83 (0.14)	−1.31 (1.00)	0.71 (0.15)	0.97 (0.00)	0.58 (0.33)	PT	1.42 (0.07)	0.01 (0.09)	0.48 (0.06)	0.96 (0.01)	0.94 (0.02)
DK	0.52 (0.14)	−1.51 (0.77)	1.32 (0.23)	0.98 (0.00)	0.71 (0.24)	RS	1.59 (0.20)	−3.06 (0.70)	1.10 (0.29)	0.97 (0.01)	0.69 (0.23)
EO	1.53 (0.20)	−4.31 (0.87)	2.51 (0.47)	0.97 (0.00)	0.64 (0.20)	SA	1.09 (0.09)	−0.27 (0.22)	0.84 (0.11)	0.95 (0.02)	0.81 (0.07)
ES	0.91 (0.05)	−0.04 (0.10)	0.21 (0.03)	0.97 (0.00)	0.91 (0.04)	SD	0.73 (0.09)	−3.59 (0.82)	1.48 (0.16)	0.99 (0.00)	0.25 (0.25)
FN	1.00 (0.10)	−1.98 (0.40)	1.51 (0.18)	0.97 (0.00)	0.66 (0.14)	SJ	0.96 (0.09)	−4.80 (0.49)	0.47 (0.09)	0.98 (0.00)	0.49 (0.35)
FR	1.33 (0.08)	0.40 (0.07)	0.33 (0.04)	0.96 (0.01)	0.97 (0.00)	SW	0.62 (0.07)	−1.93 (0.54)	0.99 (0.10)	0.99 (0.01)	0.77 (0.18)
GR	2.18 (0.14)	0.32 (0.09)	0.88 (0.10)	0.93 (0.03)	0.97 (0.00)	TK	1.44 (0.25)	−5.43 (1.04)	2.81 (0.59)	0.95 (0.01)	0.43 (0.26)
HN	0.76 (0.07)	−1.67 (0.28)	0.31 (0.06)	0.98 (0.00)	0.79 (0.16)	UK	0.73 (0.07)	−1.05 (0.36)	0.79 (0.09)	0.97 (0.00)	0.65 (0.15)
ID	1.40 (0.13)	−8.08 (0.84)	1.42 (0.23)	0.99 (0.01)	0.49 (0.35)	US	1.01 (0.07)	−0.54 (0.29)	0.65 (0.07)	0.95 (0.01)	0.69 (0.11)
IR	1.19 (0.09)	−1.56 (0.61)	1.43 (0.15)	0.99 (0.00)	0.86 (0.11)	**Mean**	1.16 (0.11)	−1.87 (0.48)	1.10 (0.17)	0.96 (0.01)	0.66 (0.17)

Notes: We have estimated a MS model with 2 states and a constant variance for each country where $dy_{tc} = \mu_1 + \varepsilon_{tc}$ for state 1 and $dy_{tc} = \mu_2 + \varepsilon_{tc}$ for state 2, dy_{tc} being the log rate growth of GDP. Standard errors in brackets.

[10]We have also estimated a MS-AR(1) model, obtaining similar results in most cases, although in some countries the results of the two models differ significantly. We prefer to maintain the MS specification because the residuals are not serially correlated for most countries. As Camacho and Perez-Quiros (2007) show, the positive autocorrelation in GDP growth rates can be better captured by shifts between business cycle states rather than by autoregressive coefficients.

3.2.2 Global model estimation

Preliminary analysis When we estimate a time series model, linear or non linear, we assume a constant distribution of the model for the whole sample. Obviously, this is also the case when we estimate a MS model for each country. We assume that the parameters, in particular the transition probabilities, which dominate the business cycle characteristics, are constant for the whole sample. We assume this even though, just looking at the Figure A1, we can see that there are major differences between the different cycles within a country. For example, in the US, the latest recession has different characteristics to the two previous ones, in terms of amplitude, duration, etc. And these recessions have major differences with respect to those before the Great Moderation. However, although major differences in the time series and structural breaks have been documented, see McConnell and Perez-Quiros, (2000) and Kim and Nelson (1999), we usually estimate models for the whole sample understanding that we are estimating an ”average” pattern for the economy with different realizations in different periods.

Nevertheless, even with these assumptions, we have shown the severe limitations that the small number of cycles available for each economy provokes in our estimates. One would like to be able to estimate an ”average” model for all the economies where we could extract lessons based, not only on six or seven cycles but on more than 100 complete cycles. That would imply having the same data generating process for all the economies, with different realizations, which could explain the differences observed across countries.

To check to what extent that assumption is plausible or at least, whether it is no less plausible than the one that we make when estimating a time series in an economy, we need to see if the time series heterogeneity within each country is bigger than the heterogeneity across countries. To do so, in the same way that we have a natural division of all the recessions and expansions of our dataset in 33 different countries, and we can calculate the characteristics of the business cycle in each country, we divide the sample into 30 time intervals of equal duration and we check the characteristics of the recessions and expansions that appear for all the 33 countries in each of those 30 intervals of 8 quarters' duration[11]. For example, the first interval represents the period 1950.1-1952.1 and we calculate the characteris-

[11] We use 30 intervals in order to be closer as possible of the number of countries.

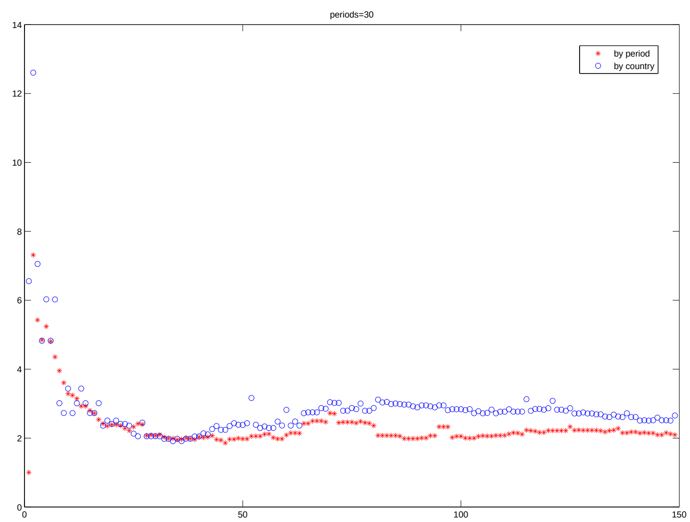
tics of the recessions during that period; interval 2 collects the recessions form the next two years, and so on. In the end, we have distributed all the recessions that we have in our sample into 30 intervals (or periods), but instead of being classified by country, they are classified in a temporal fashion.

TABLE 3
KRUSKAL-WALLIS TEST

	DURATION	AMPLITUDE	CUMULATION	EXCESS
By country	29.09 (0.6146)	42.85 (0.0953)	38.35 (0.2035)	41.97 (0.117)
By periods	50.39 (0.0082)	64.62 (0.0002)	59.08 (0.0008)	43.40 (0.0418)

Notes: p-values of the null hypothesis of equality across countries (grouping by countries) or across periods (grouping by periods) in brackets; for periods the sample has been split into 30 groups.

In order to formally test the hypothesis that the differences by country are not bigger than the differences in time, we use two statistical tests. First, we apply the Kruskal-Wallis test (an extension of the rank sum Wilcoxon test for the multivariate case) that compares samples from two or more groups and tests the null hypothesis that all the samples are drawn from the same population. Notice that, when we group recessions by countries, we test the null of equality across countries, and when we group them by periods, we test the null of equality across periods. We apply this test by countries and periods for the 4 characteristics of the recessions. The results, displayed in Table 3, show that we accept that all the countries come from the same population for all the characteristics at 5% significance, but we reject that hypothesis in the time series dimension. For example, for duration, grouped by country, we accept the null that all the countries are the same with a p-value of 0.61 but we reject the null of equal durations by periods with a p-value of 0.01. In order to summarize the information of all the features of a recession, we have calculated the Euclidean distance for each recession with respect to its country-group (recessions in the same country) and its period-group (recessions in the same period). The results are presented in Figure 2. The X axis represents each of the recessions in our sample, and each of the two lines represents the Euclidean distance to its country average and its period average (taking into account the 4 features that we are considering). As can be seen, for most recessions the distance is lower and, therefore, the similarity higher, to its period than to its country.



In the X axis we display the different recessions. Black circles represent the distance of the characteristics of each crisis to its period, and the white ones to its country.

FIGURE 2. Euclidean distance between business cycle characteristics by groups of countries and periods

Second, we mix all the recessions and make clusters with similar characteristics. We have selected four clusters based on the silhouette plot, which displays a measure of how similar each point is to points in its own cluster compared to points in other neighboring clusters. After that, we analyze the concentration of periods and countries in each cluster using the Herfhindal index. We find a greater concentration of periods than of countries for all the characteristics. So, it can be concluded that there are more similarities in the same period than in the same country (Table 4).

Therefore, we can conclude that there is less heterogeneity across countries than in a time series dimension. So, if, when we estimate a time series, we have no problem in mixing heterogeneous features, it should not be a problem to build a ”virtual country” that includes all the countries and periods of the sample. As we mentioned above, our idea is that this strategy is feasible and will lead to a significant reduction in the uncertainty of parameter estimates.

In order to mix the countries, we denote as dy_{jc} the GDP growth of country c in period t, T_c being its sample size. First, we construct the succession of growth rates

TABLE 4

HERFHINDAL INDEX OF CLUSTERS

	DURATION	AMPLITUDE	CUMULATION	EXCESS	MEAN
CLUSTER 1					
By country	0.0657	0.0657	0.0527	0.0355	0.0571
By periods	0.0865	0.1142	0.0566	0.0383	0.0633
CLUSTER 2					
By country	0.0359	0.0417	0.0495	0.0481	0.0483
By periods	0.0444	0.0445	0.0815	0.0872	0.0535
CLUSTER 3					
By country	0.0741	0.0453	0.0430	0.0440	0.0741
By periods	0.1111	0.0453	0.1167	0.0440	0.1111
CLUSTER 4					
By country	0.0492	0.0488	0.0384	0.0381	0.0363
By periods	0.0446	0.0446	0.0401	0.0394	0.0463
MEAN					
By country	0.0479	0.0626	0.0693	0.0810	0.0488
By periods	0.0533	0.0671	0.1103	0.1885	0.0533

Notes: Higher numbers imply more concentration of countries or periods in each cluster; for periods the sample has been split into 30 groups.

of all countries

$$dY = \{dy_{tc}\}_{t=1:T_c;\, c=1:n} = \{dy_{11},...,dy_{T_1 1},...,dy_{1c},...,dy_{T_c c},...,dy_{1n,...},dy_{T_n n}\} \quad (5)$$

where $T = \sum_{c=1}^{n} T_c$ and n is the number of countries. After calculating the mean and standard deviation of dY, we standardize each country and obtain

$$d\widetilde{Y} = \{d\widetilde{y}_{tc}\}_{t=1:T_c;\, c=1:n} = \{d\widetilde{y}_{11},...,d\widetilde{y}_{T_1 1},...,d\widetilde{y}_{1c},...,d\widetilde{y}_{T_c c},...,d\widetilde{y}_{1n,...},d\widetilde{y}_{T_n n}\} \quad (6)$$

where $\{d\widetilde{y}_{tc}\} = \{dy_{tc}\}$ with the mean and standard deviation of dY and construct the series of our "virtual country", $\widetilde{Y}_r$, as follows:

$$\begin{aligned} \widetilde{Y}_0 &= 100 \\ \widetilde{Y}_r &= \widetilde{Y}_{r-1}(1 + d\widetilde{y}_{tc}/100),\ r = 1,...T;\ t = 1,...T_c;\ c = 1...n \end{aligned} \quad (7)$$

Now, we explore the performance of the BB procedure when we use our "virtual country" ($\widetilde{Y}$) (that includes all the countries and periods and has a sample size of

5,000, and we obtain 149 periods of recession. We show that the result of applying the turning point algorithm to this ”virtual country” is almost the same as those of estimating each country individually, but with small differences appearing in the links between countries. We have also carried out a small experiment, randomly drawing the order of the countries. We check the matching of turning points with 1,000 random orders of the countries and find that the error is less than 1%[12].

Model estimation We estimate, as in the country model, a MS model with two states as defined in (4) to our ”virtual country” ($d\widetilde{Y}$) as defined in (6). We obtain results that are in line with the literature, with transition probabilities equal to 0.97 and 0.65 and expansion and recession means that are very close to the mean of the country estimates. The parameter estimates are displayed in Table 5[13]. It is noteworthy that the standard errors associated with the probability of recession are considerably lower than those obtained with the country specification. This model also computes the probabilities of expansion and recession in every country and every period of time. The data and probabilities of this global model are displayed in Figure 3. Obviously, in this figure it is difficult to distinguish each country because we are plotting 5000 observations corresponding to all the countries, one after the other. However, if we compare these global probabilities, after retrieving them for each country, with those obtained for the country model (CM), we find that the correlation is very high in most countries with the exception of those with atypical behavior (Table 6, first column). The conclusion is that we have “normalized” their behavior by integrating it into something like a ”population of recessions”. This argument has a Bayesian interpretation because it is equivalent to introducing a prior into the parameters of the countries. This prior correspond, for each country ”i”, to the parameter distribution of the model estimated for all the countries excluding country ”i”.

[12]Obviously the differences among each of the random orders come in the links between countries. Depending on the evolution of the next country, we will date a recession or not. However, the links between two countries represent only 28 observations (30 countries minus two extremes) which is approximately 0.5% of the observations.

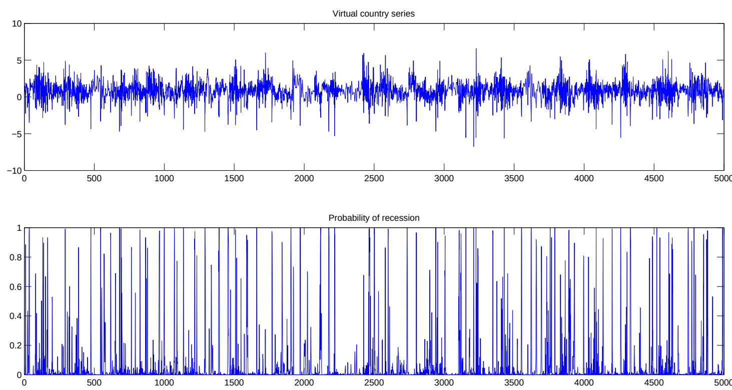
[13]Given that we are aware of the problem of the link between each pair of countries on the dynamics of the global series, to test the robustness of the results, we have not considered the first 20 observations for each country in the maximization of the likelihood function. Additionally, we have performed a stationary bootstrap, following the method of Politis and Romano (1994). In both cases, the parameter estimates are very similar.

TABLE 5

GLOBAL MODEL ESTIMATION

μ_1	μ_2	σ^2	p	q	δ_1	δ_2
			MS MODEL			
0.97 (0.018)	-1.46 (0.122)	1.09 (0.025)	0.97 (0.001)	0.65 (0.035)		

Notes: We have estimated a MS model with 2 states and a constant variance for the global model where $\widetilde{Y}_r = \mu_1 + \varepsilon_r$ for state 1 and $\widetilde{Y}_r = \mu_2 + \varepsilon_r$ for state 2, $\widetilde{Y}_r$ being the log rate growth of GDP of the "virtual country". Standard errors in brackets.



In the top graph we display the observations of the "virtual country" that consists in the concatenation of the GDP growth rates (previously standardized) of all the countries; the bottom graph displays the probability of being in recession with this global model estimation.

FIGURE 3. Probability of recession with global model

Furthermore, we compare the turning points computed with the Bry Boschan algorithm, that we use as the reference series, with the probabilities estimated for the country model and the global model and find that the quadratic probability scores (QPS)[14] fall dramatically when we use our virtual-global country. On average, the QPS of the difference between the recession indicator of the BB algorithm and that estimated with the MS country model is 0.15 while, in the case of the MS estimated for the virtual country, it is 0.08 (Table 6 column 2 and 3). The intuition of why there is such a strong reduction in the QPS can be seen analyzing the case of France.

[14]To compute them, we use the definition of Quadratic Probability Score (QPS) of Diebold and Rudebusch (1989), $QPS = 1/T\sum_{t=1}^{T}(Pt - BBt)^2$accuracy. This measure is similar to mean square errors for the case of probabilities. When Pt refers to a forecast value, we denote it by FQPS (Forecasting Quadratic Probability Score).

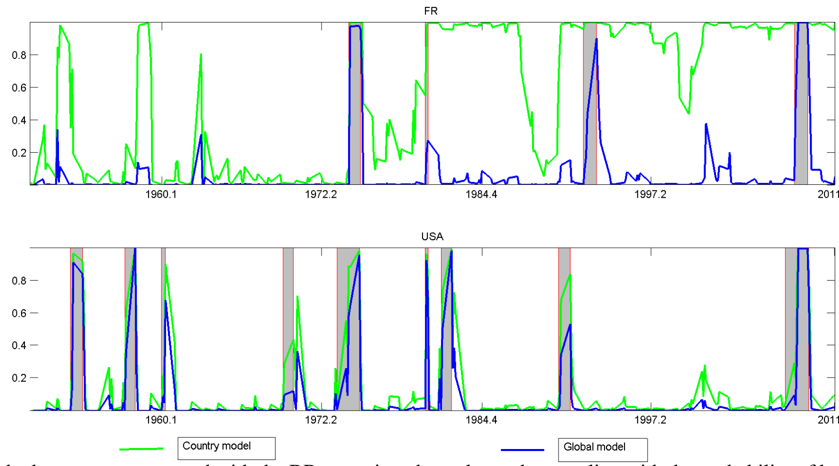
TABLE 6
CORRELATIONS AND QPS

	CORRELATION	MSE	
	MS_country-MS_glob	country_prob	global_prob
AG	0.71	0.04	0.16
AU	0.95	0.08	0.08
BD	0.86	0.15	0.12
BG	0.40	0.38	0.03
BR	0.95	0.21	0.20
CL	1.00	0.04	0.04
CN	0.96	0.02	0.02
CZ	1.00	0.09	0.08
DK	0.97	0.19	0.19
EO	0.98	0.11	0.10
ES	0.71	0.11	0.03
FN	1.00	0.08	0.08
FR	0.35	0.44	0.02
GR	0.30	0.43	0.11
HN	0.96	0.10	0.08
ID	0.73	0.04	0.01
IR	0.93	0.06	0.06
IS	0.78	0.09	0.02
IT	0.24	0.50	0.12
JP	0.21	0.63	0.04
LX	0.98	0.08	0.09
MX	0.57	0.12	0.06
NL	0.95	0.09	0.08
OE	0.86	0.08	0.06
PT	0.57	0.21	0.04
RS	0.98	0.03	0.03
SA	0.77	0.05	0.09
SD	0.79	0.14	0.11
SJ	0.86	0.05	0.03
SW	0.89	0.11	0.09
TK	0.99	0.23	0.22
UK	0.99	0.08	0.09
US	0.95	0.04	0.05
TOTAL	0.79	0.15	0.08

Notes: QPS of the difference between BB states and MS probabilities. Correlation between MS probabilities.

CM=country model; GM=global model

Figure 4, top panel, plots the recession probabilities obtained with the global model and the recession probabilities obtained by estimating the country model for the French economy. In addition, we plot the recession periods estimated using the BB algorithm. As can be appreciated, the global model perfectly matches the BB turning points contrary to what happens with the country model recession probabilities. The short sample and the characteristics of the French data make it very difficult for the MS to obtain a proper convergence. In that sense, the priors that come from the rest of the world help to fit the recession dates more properly. However, in the case of US, (Figure 4, bottom panel) the difference is not so important and the country and global model probabilities of recessions are highly correlated.



The shadow areas correspond with the BB recession chronology; the gray line with the probability of being in recession according to the country model; the black line according to the global model.

FIGURE 4. Comparing recession probabilities in France and USA

So, we have shown that we can mix countries and take advantage of a ”virtual country” country with 5,000 observations. The estimation of recession probabilities leads to similar results to those obtained with BB methods and so we have a powerful tool for analyzing recessions that allows us to make inferences about the future and that dramatically reduces the uncertainty in the estimation of the parameters.

We are aware that, so far, we have ignored one of the most important features of the international business cycle data. The well-known fact that there are important co-movements in the economic time series across countries. Appendix 2 shows how we have handled this issue. As we explain there, we explore two avenues: First, we have introduced a new ingredient into our model, the dependence of each country’s economy cycle on what happens in the rest of the world. Second, we have incorporated co-movements across countries in a panel estimation. The first option give us non-significant and wrongly-signed coefficients. The second, shows that the danger of a possible misspecification of the nature of co-movements could lead to a massive loss of fit in the model. Therefore, the GM proposed before stands as the most robust framework to deal with all possible cross-dependence across countries.

Analyzing forecast performance This section provides a detailed analysis of the forecasting ability of the model that we have carried out before introducing the financial variables. Starting with an initial sample running from 1950.1 to 1969.4, we recursively increase the sample adding one more observation for each country in every period until the last minus one period. Notice that, at each step, we construct the global series with the countries that have information in this period and, consequently, the quality of the data and the reliability of the results increase at each step. This recursive exercise allows us to calculate the out-of-sample forecast one period ahead in each iteration for each country. Calling P_{tc} the conditional probability at time t, of being in a recession, the probability of $t+1$ being in a recession is $P_{t+1c} = (1-p_t)(1-P_{tc}) + q_t P(_{tc})$ where p and q are re-calculated in each iteration of the recursive algorithm.

To judge the true predictive efficacy of the model, it is interesting to compare the forecast that we obtain estimating each country individually with the result of using the global model. As our BB model represents the benchmark description of the economy, we use the results of applying the BB algorithm and calculate the FQPS and the Diebold and Mariano (1995) test for predictive ability (DM)[15]. Probabilities of recession estimated with the global model match the BB states better than country estimates. The FQPS that compares the recession probabilities of the country estimation with the BB turning points is significantly higher (around double) than that obtained with the global model (0.29 and 0.14, respectively). Furthermore, the results of the DM test show that this difference is significant when we compare the country with the global model (the value of the statistic is 9.16 with a p-value of 0.000).

To sum up, we have built a global model that gathers all the information available about the crises at time t from different countries and different periods. We have shown that this course of action is legitimate because we found more similarities between recessions produced in the same period than in different periods in the same country. We have shown the robustness of the model to different estimation methods, especially parametric techniques, and the advantages that it offers in terms of reducing uncertainty and increasing the ability to forecast. Furthermore, this approach considers the business cycle as an endogenous variable where recessions are not punctual and exogenous facts as the literature normally assumes. In short, we have obtained a tool that describes the dynamics of recession and expansions well, and is able to infer future states of the economy based on the information of 149

[15]We have also applied the Giacomini and White (2006) test for conditional predictive ability using a rolling procedure and the conclusions are similar.

recession periods. Now, it is time to allow for the possibility of credit to modify that framework, a matter that will be discussed in the next section.

3.3 Inferring the future with credit

The purpose of this section is to assess the effect of financial variables on the economic cycle. We have selected credit as a reference variable and we have built the ratio of domestic credit divided by nominal GDP in local currency (cr_{ti}) for time t and country i. This variable has been used in the most relevant empirical literature that studies financial crises [Gourinchas and Obstfeld (2011); Rose and Spiegel (2011) and Claessens et al. (2011b, c), among others]. Both the domestic credit series, defined as "claims on private sector of depositary corporations", and nominal GDP have been collected from the International Monetary Fund (Financial Statistics, IFS) and require some adjustment, such as removing seasonality (in nominal GDP), matching exchange rates and homogenizing units [16]. We present the results of the analysis using the level of credit to GDP ratio as the previously quoted authors do. We also estimate all the results with variation in credit to GDP ratio, and in this case the key coefficient is not significant. This is why we present the results of the levels, where the departure from the model without credit are clearer and more significant[17].

The final sample size of the domestic credit ratio is conditioned by the length of the two series, especially that of nominal GDP, which is available for a shorter sample for most countries. Therefore, to use the global model as a benchmark, we need to reestimate the global model for the available sample, about 4,000 observations, obtaining similar results to those in the previous section[18]. In parallel, we have built the global series for domestic credit, called CR_t, where t=$1,\ldots,T$ and T is the global sample size, the sum of the number of observations for each country[19].

[16] We have used the TRAMO-SEATS package (Gomez and Maravall, 1996) for the seasonal adjustment of the series.

[17] We estimate the model with and without standarizing the series of credit to GDP ratio to have the same mean and variance for each country. The standardization of the series does not affect the results. We present the results without the standarization.

[18] Details about the length of the domestic credit and nominal GDP series are presented in Appendix 1.

[19] For simplicity of the notation we are going to denote by "t" the time-country index that we denoted by "r" in (7).

3.3.1 In-sample analysis

Credit can affect the dynamics of the business cycle by modifying either the means of the states, μ_1 and μ_2, or the transition probabilities, p and q.

The specification for the time-variant mean has the following expression:

$$\begin{aligned} d\widetilde{Y}_t &= \mu_{s_t,t} + \varepsilon_t \\ \mu_{1t} &= \mu_1 + \alpha_1 * CR_{t-1} \text{ for state 1} \\ \mu_{2t} &= \mu_2 + \alpha_2 * CR_{t-1} \text{ for state 2} \end{aligned} \tag{8}$$

The second specification corresponds to a time-variant transition probability model (TVTP) with the following expression:

$$\begin{aligned} p_t &= p + \delta_1 * CR_{t-1} \\ q_t &= q + \delta_2 * CR_{t-1} \end{aligned} \tag{9}$$

Notice that we include the credit ratio with a lag in order to use this information for forecasting at time t. Table 7 summarizes the results of estimating the baseline model, without introducing credit, the model with time-varying state means, the model with time-varying transition probabilities and the model that includes both time-varying means and probabilities[20]. The effect of credit on the means of states, measured by $\widehat{\alpha}_1$ for expansions and by $\widehat{\alpha}_2$ for recessions, is negative and significant in both cases (-0.37 and -0.50, respectively). This means that an increase in the credit ratio reduces the growth in expansions and increases the fall in recessions. A similar picture is obtained when we study the influence of credit on the transition probabilities, p and q. We find a negative but small and not significant effect on the probability of being in expansion, and a positive and significant effect on the probability of being in recession. This result implies that the higher the credit to GDP ratio, the longer the expected duration of the recession period. We do not consider the model that includes the credit to GDP ratio affecting both the mean of the states and the probabilities because, as can be seen in Table 7, fourth line, the

[20] The estimated coefficients for the model without credit appear in the first row of the Table 7 and change marginally with respect to those displayed in Table 5, due to the reduction of the sample after the introduction of the credit.

TABLE 7

GLOBAL MODEL ESTIMATION WITH CREDIT

μ_1	μ_2	σ^2	p	q	δ_1	δ_2	α_1	α_2	θ
MS MODEL WITH FIXED MEANS AND PROBABILITIES									
0.87	−1.84	1.01	0.97	0.60					
(0.019)	(0.112)	(0.026)	(0.010)	(03804)					
MS MODEL WITH FIXED PROBABILITIES AND TIME-VARYING MEANS									
1.15	−1.41	0.99	0.97	0.60			−0.37	−0.50	
(0.037)	(0.194)	(0.026)	(0.001)	(0.037)			(0.043)	(0.215)	
MS MODEL WITH FIXED MEANS AND TIME-VARYING PROBABILITIES									
0.87	−1.84	1.01	0.97	0.50	−0.04	0.11			
(0.019)	(0.12)1	(0.027)	(0.00)	(0.068)	(0.003)	(0.057)			
MS MODEL WITH TIME-VARYING MEANS AND PROBABILITIES									
1.17	−1.26	0.99	0.96	0.55	0.02	0.06	−0.40	−0.73	
(0.035)	(0.183)	(0.026)	(0.000)	(0.069)	(0.003)	(0.076)	(0.039)	(0.210)	
MS MODEL WITH FIXED PROBABILITIES AND TIME-VARYING MEANS (2008.3)									
1.19	−1.04	0.93	0.96	0.69			−0.34	0.35	
(0.041)	(0.152)	(0.027)	(0.000)	(0.035)			(0.048)	(0.196)	
MS MODEL WITH FIXED MEANS AND TIME-VARYING PROBABILITIES (2008.3)									
0.97	−0.73	0.95	0.96	0.64	−0.00	0.10			
(0.026)	(0.129)	(0.028)	(0.000)	(0.053)	(0.008)	(0.063)			
MS MODEL WITH DURATION DEPENDENCE									
0.87	−1.81	1.02	0.97	0.69					−0.09
(0.023)	(0.187)	(0.036)	(0.001)	(0.044)					(0.044)
MS MODEL WITH DURATION DEPENDENCE AND TIME-VARYING MEANS									
1.16	−1.28	0.99	0.97	0.69			−0.38	−0.65	−0.09
(0.013)	(0.101)	(0.021)	(0.004)	(0.045)			(0.025)	(0.084)	(0.042)

Notes: We have estimated a time-varying transition probability (TVTP) Markow switching model where $p_t = p + \delta_1 * CR_{t-1}$ and $q_t = q + \delta_1 * CR_{t-1}$ where CR is the ratio of credit to GDP and a model where CR affects the means of the two states, $\mu_{1t} = \mu_1 + \alpha_1 * CR_{t-1}$ and $\mu_{2t} = \mu_2 + \alpha_2 * CR_{t-1}$. In addition, a duration-dependence model has been estimated, where θ means the effect of the duration of the current recession. Standard errors in brackets.

coefficient of the time-variant probability parameters have the wrong sign, making it clear that the model presents specification problems. In terms of the in-sample analysis, the results of fitting the recession periods show that the inclusion of the financial variable leaves unaffected the average QPS.

Additionally, as we mentioned before, we are interested, not only in inferring future probabilities, but also in understanding the effects of credit on business cycle characteristics. So, we have calculated the duration, amplitude and cumulation for the two cyclical phases and the three models considered: the baseline without credit, the model that considers means of states depending on credit and the model that allows the probabilities to vary over time depending on the evolution of credit. For time-varying parameters, we define the duration (D), amplitude (A) and cumulation (C) of recessions as follows[21].

If μ_2 is time-varying, the expected growth in recessions will be a weighted average of the growth in each period of time, where the weights are defined by the

[21] Notice that, in a MS model, the excess is equal to zero.

probability of being in a recession in each period t,

$$E(\mu_2) = \sum_{t=1}^{T} \mu_{2t} P(rec_t) / \sum_{t=1}^{T} P(rec_t)$$

Given that the transition probabilities are constant, the formula for duration is the standard one, $E(D) = 1/(1-q)$. Therefore, the amplitude and the cumulation will be just

$$E(A) = E(\mu_2)/(1-q)$$

$$E(C) = E(\mu_2)/2*(1-q)^2 \tag{10}$$

If q is time-varying, the expected duration will be a weighted average of the duration in each period of time.

$$E(D) = \sum_{t=1}^{T} d_t P(rec_t) / \sum_{t=1}^{T} P(rec_t), \text{ where } d_t = 1/(1-q_t)$$

$$E(A) = \mu_2 E(D)$$

$$E(C) = \mu_2 (E(D))^2/2 \tag{11}$$

where $P(rec_t)$ is the probability of being in recession at each time t in country c.

In fact, the figures of the three features are very similar for all the models. In the case of recessions, the introduction of credit into the means of states has a positive but small influence on recessions and a negative but also small effect on the transition probabilities. Similar conclusions are obtained in the case of expansions (see Table 8).

But it is convenient to clarify that the above results reflect the average behavior. If we look at the effect over the whole range of values of credit and focus on the extreme values, we conclude that, perhaps, on average the effect of credit is small, but it could have important effects on the extreme values. Figure 5 shows the evolution of the effect of the credit ratio on business cycle features in both the mean time-varying and probability time-varying models. In the first case, when credit

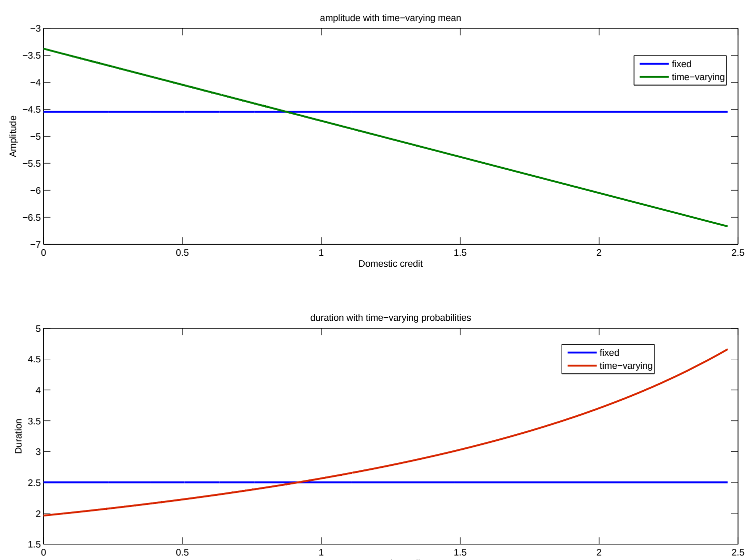
TABLE 8

EFFECT OF CREDIT ON BUSINESS CYCLE FEATURES

MODEL	*DURATION*	*AMPLITUDE*	*CUMULATION*
RECESSION			
MS Model with fixed means and probabilities	2.50	−4.61	−5.77
MS Model with fixed probabilities and time-varying means	2.49	−4.41	−5.50
MS Model with fixed means and time-varying probabilities	2.55	−4.70	−5.99
MS Model with duration dependence	2.78	−5.03	−6.99
MS Model with duration dependence and time-varying means	2.83	−4.92	−6.99
EXPANSION			
MS Model with fixed means and probabilities	35.26	30.60	539.54
MS Model with fixed probabilities and time-varying means	33.16	28.96	480.14
MS Model with fixed means and time-varying probabilities	34.88	30.29	528.18
MS Model with duration dependence	36.62	31.81	582.51
MS Model with duration dependence and time-varying means	35.19	24.71	434.89

Notes: Duration in quarters.

reaches maximum values above 2, the amplitude of the recession is -6.7, which is an almost 50% increase over the average value of -4.5. Similarly, the duration may be up to 4.5 quarter when credit has extreme values, compared to the 2.5 that the average values recorded. Notice that, in this case, the path is exponential due to the non-linear relationship between probability and duration.



The top graph displays the path of amplitude according to the time-variant mean model; the bottom graph the path of duration according to the time-variant probability model.

FIGURE 5. Effect of credit on extreme values

Therefore, this section reconciles our results with the standard results in the recent literature. It seems that credit affects probability of being in recession. Credit to GDP ratio is a significant variable in both the specification of the mean and transition probabilities. We show that credit matters even in a context where the recessions periods are not exogenously given. But, if the relation between credit and forthcoming recessions is so clear, the question asked by the Queen of England is completely relevant. Why did nobody see the recession coming?

3.3.2 Out-of-sample

To see the recession coming implies being able to forecast future economic developments in $t+k$ with the information available in period t. Given the previous results, the natural candidate to use as an indicator of what is coming is the credit to GDP ratio. The main goal of this section is to assess up to what point, there is a marginal gain in the forecasting ability of the models that include the credit to GDP ratio versus the models that do not take credit into account. More specifically, we analyze the ability to forecast both the probability of entering into recession and the business cycle characteristics of the global model (GM); the global model that considers time-varying means depending on the credit rate (GM_credit_μ); and the global model that considers time-varying transition probabilities depending on the credit rate (GM_credit_prob). As usual, we consider the BB model as our benchmark model. We have also carried out the analysis for the country model, but this model performs very badly in comparison with the different global models and, so, we have not included the results in the tables[22].

We have followed a similar procedure to that described in previous sections, recursively estimating the model with an initial sample running from 1950.1 to 1969.4 and calculating, in each iteration, the probability of recession at time $t+1$ with information at time t and the features of the recession with the parameters estimated at time t. The main conclusion is that there are no important differences between the forecasting ability of the global models. The first row of Table 9 shows this lack of differences using the Forecasted QPS (FQPS). More formally, the Diebold and Mariano (1995) test, shows that neither the model with probability that consid-

[22] To avoid the inclusion of more tables, there are two more models in the comparison that we will introduce later in the text but they already appear in the table. We will talk about these models later.

ers time-varying means depending on the credit rate (GM_credit_μ); nor the global model that considers time-varying transition probabilities depending on the credit rate (GM_credit_prob) improve the results of the GM model. The results are displayed in the first two squares of Figure 6. Each block presents the FQPS of the model in the row, the FQPS of the model in the column and the results of the Diebold and Mariano test of equal values. As can be seen, the GM model is not worse than any of the two candidates, the (GM_credit_μ) and the GM_credit_prob) models. The second one presents even significantly higher FQPS than the GM model[23].

TABLE 9

FORECASTING BUSINESS CYCLE CHARACTERISTICS

	GM	GM_credit_μ	GM_credit_$prob$	GM_dd	GM_dd_credit_μ
FQPS	0.11	0.11	0.11	0.11	0.11
FQPS at turning points (1,2.period, total)	0.45	0.44	0.44	0.43	0.43
MSE duration recessions at first point	9.84	10.36	11.14	8.74	9.23
MSE amplitude recessions at first point	20.47	22.60	21.47	19.52	20.69
MSE cumulation recessions at first point	494.14	505.78	511.65	473.72	482.92

Notes: FQPS of the difference between BB states and MS forecast probabilities. MSE of the difference between BB characteristics and MS forecast characteristics.

This impression does not change when we consider the effect of credit on the forecasting of business cycle characteristics. We have extracted the observations corresponding to recessions from the global series, following the BB chronology, and we have studied several indicators, which are shown in Table 9. The following rows of this table display the results of forecasting recession features at the beginning of the recession. For all the characteristics, duration, amplitude and cumulation, the GM presents smaller forecasted MSE when comparing the forecast made by the three models on the first quarter of recession period and the realization of the characteristics in those recessions. So, the inclusion of the credit ratio has no significant effects on forecasting recession characteristics.

In short, even though we saw before that, in-sample, there was a relation between credit and recessions, there is no way to exploit this relation in an out of sample experiment and, therefore, a policymaker can neither improve the inference about the state of the economy in $t+1$ with the information about credit in period t

[23] We repeat the exercise concentrating on the predictive power of the different models on the first two periods of the turning points. The GM presents similar FQPS to the GM_credit_μ and the GM_credit_prob models.

nor forecast the characteristics of forthcoming recession with this variable[24].

But then, why are the in-sample results so clear and the out of sample results, which are the ones that are needed to infer the future, so poor? The following exercise could shed some light on this.

3.3.3 In-sample analysis. 2008.3

We now repeat the previous in-sample analysis but just at the beginning of the Great recession. The first quarter of the recession period, according to the NBER, is, for the US 2008.1. According to the CEPR, for the Euro Area, it is 2008.2. The rest of the countries also start the recession around those dates. With these dates in mind, we estimate, for 2008.3, the first quarter in which most of the countries are in recession, the models that have focused our analysis in the previous section, the model with time-varying state means and the model with time-varying transition probabilities. We choose this date because it coincides exactly with the available sample when the Queen of England formulated her question. The results are displayed in rows five and six of Table 7.

As can be seen in the table, one of the coefficients for the time-varying state means model has the opposite sign to the expected one (+0.35) indicating that more credit implies less negative growth rates in recession periods. The model with time-varying probabilities gives non-significant results for the coefficients δ_1 and δ_2.Therefore, the evidence that links credit and recessions, even though it is clear with the latest available information, was not clear before the Great Recession. The in-sample results for the sample until 2011 are basically driven by the coincidence, in the latest recession, of a financial and real crisis in most of the countries in our sample. But this evidence was not present in the data when the Queen asked her question. This is why nobody saw what was coming. This is also why the results of the out of sample analysis show the impossibility of exploiting the relation between credit and growth to make inference about the future.

[24] We understand that not all crises have a financial origin and that may bias our results towards not finding significant effects of credit. To confirm this hypothesis, we repeat the forecasting exercise using only those recessions (selected with the BB algorithm) that coincide with the financial crises documented in Gourinchas and Obstfeld (2011). Our results show that the forecasting performance of the different models is very similar, because we reach the same conclusion. Credit does not help to forecast recessions that have a financial nature.

3.3.4 Duration dependence

The fact that the out of sample results are so disappointing made us think that, perhaps, it is just impossible to improve the results of the GM. It might be that the uncertainty associated with recessions is so high that the null hypothesis of no improvements will always be accepted for all the dimensions in which we try to extend the GM.

In order to test this, we introduce a new ingredient into our global model in order to gauge the robustness of the effect of credit. So far we have considered that the duration of the recession is fixed. However, it is plausible to think that its expected duration may depend on how long the country has been in recession. This idea was introduced by Diebold and Rudebusch (1990) and developed in the MS framework by Durland and McCurdy (1994) and Filardo and Gordon (1998) who extend the model of Hamilton (1989) to allow state transition to be duration-dependent. More specifically, we only consider the effect of previous duration in the transition probability of recessions[25]. So, the expression of the probability of staying in recession is $q_t = q + \theta \sum_{i=1}^{d} P(rec_{t-i})$. We have considered a maximum value of d=8, based on the results obtained with the BB method.[26] We have also combined the mean time-varying model depending on credit with the duration-dependence probability of being in recession [27]. The results of estimating the two models appear in lines 7 and 8 of Table 7. We can see that the parameter of duration dependence is negative and significant, which means that, as we expected, the probability of being in recession decreases, the longer the recession has lasted. Although the value of the parameter is small, -0.09, notice that its effect increases as the recession progresses so that, when a country has spent 2 quarters in recession, the probability decreases by 0.18, when it has spent 3 by 0.27 and so on up to 0.7, which reduces the probability to zero. The introduction of the credit variable into the means of the states barely changes the value and significance of the duration-dependence parameter. Furthermore, the parameters corresponding to time-varying means are similar to those of the previous model, which shows the robustness of the estimation.

[25]We are especially interested in recessions. Furthermore, the duration-dependence parameter is not significant for expansions.

[26]The histogram of duration shows that most values are concentrated in the interval 2-6, the mean duration is 4 and only a few values higher than 8 can be found.

[27]The results of mixing duration-dependent probability models and time-varying transition probabilities with credit imply specification problems and not stable solutions.

What is interesting about this specification is the out of sample performance. The results of the analysis are displayed in the last two columns of Table 9 and the two-by-two formal statistical comparisons with the rest of the model is presented in Figure 6. The model that only contains the duration dependence is denoted by GM_dd. The model that contains duration-dependence and mean time-varying depending on credit is denoted by GM_dd_credit_μ. As can be seen, the GM model is clearly outperformed by GM_dd which is also better than GM_dd_credit_μ (although not significantly). Therefore, the GM forecasting performance can be statistically improved, but not in the direction of including credit.

	GM	GM_credit_μ	GM_credit_prob	GM_dd	GM_dd_credit_μ
GM		FQPS1=0.1110 FQPS2=0.1140 DM_test=-1.4507 (0.2786)	FQPS1=0.1110 FQPS2=0.1168 DM_test=-2.6116 (0.0264)	FQPS1=0.1110 FQPS2=0.1058 DM_test=3.7780 (0.0006)	FQPS1=0.1110 FQPS2=0.1068 DM_test=2.1192 (0.0845)
GM_credit_μ			FQPS1=0.1140 FQPS2=0.1168 DM_test=-0.769 (0.5933)	FQPS1=0.1140 FQPS2=0.1058 DM_test=3.5593 (0.0004)	FQPS1=0.1140 FQPS2=0.1068 DM_test=5.3019(0.0000)
GM_credit_prob				FQPS1=0.1168 FQPS2=0.1058 DM_test=4.4121 (0.0000)	FQPS1=0.1168 FQPS2=0.1068 DM_test=2.7186 (0.0198)
GM_dd					FQPS1=0.1058 FQPS2=0.1068 DM_test=-0.5499(0.6859)
GM_dd_credit_μ					

Notes: The first value corresponds with rows and the second with columns.

FIGURE 6.Comparing forecasting of probability of recessions (Diebold and Mariano test)

This good out of sample performance of the GM_dd model also extends to the forecasting of the business cycle characteristics. For amplitude, duration and cumulation, GM_dd is, again, significantly the best. So, the conclusion is that the GM_dd model is the best of the global models in terms of forecasting and leads to significant improvements with respect to GM. Summing up, the conclusion of the out-of-sample analysis is that the credit ratio does not play a role in forecasting either the probability of recessions or their characteristics. Both the descriptive analysis and the posterior statistical analysis have shown that, the model that takes dependence duration into account in the probability of recessions is the best in all cases, beating the rest of the models. [28]

4 Conclusions

In this paper, we analyze why economist failed to forecast the Great Recession. We illustrate this failure looking at one of the most cited and relevant variables in this analysis, the now infamous credit to GDP chart. We find that credit build-up exerts a significant and negative influence on economic growth, both in expansion and recession, increases the probability of remaining in recession and reduces that of continuing in expansion. However, these effects, are mainly driven by the latest recession. The comparison of the forecast performance of models that include credit with other global models show that there is no significant gain as a consequence of introducing credit. Therefore, in contrast to previous literature, our results indicate that the role of credit in the identification of the economic cycle and its characteristics is very limited.

Our results explain why financial accelerator mechanisms have not played a central role in models to describe business fluctuations. The financial accelerator was not a key point in explaining business fluctuations because empirically it did not have such a close relation with the business cycle, both in sample (previous to the crisis) and in an out of sample approach, once the uncertainty in dating recession periods is included in the model. So, with the full sample, credit can describe the past but not infer the future.

[28] According to the IMF (2011) report, even though variation in the credit to GDP ratio is a good indicator of recession, when this variable is combined with asset prices, the results are more robust. We have checked the interaction effect of credit with other variables such as stock returns and housing prices on the probability of recession and expansion. We have introduced the variables in three ways. First, we incorporate credit and one additional variable in the same model. Second, we include the product of credit and each of the other two variables. Finally, we consider credit only when the value of stock returns or housing prices is above a threshold value (quantile 75 or 90). In no case, do we find any important effect that increases the significance of credit.

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Appendix 1. The data

TABLE A.1
GDP DATA

COUNTRY	ACRONYM	SAMPLE SIZE
Argentina	AG	1993.1 – 2011.2
Australia	AU	1959.3 – 2011.2
Germany	BD	1960.1 – 2011.2
Belgium	BG	1960.1 – 2011.2
Brazil	BR	1990.1 – 2011.2
Chile	CL	1986.1 – 2011.2
Canada	CN	1960.1 – 2011.2
Czech Republic	CZ	1995.1 – 2011.2
Denmark	DK	1991.1 – 2011.2
Estonia	EO	1993.1 – 2011.2
Spain	ES	1970.1 – 2011.2
Finland	FN	1960.1 – 2011.2
France	FR	1950.1 – 2011.2
Greece	GR	1960.1 – 2011.2
Hungary	HN	1995.1 – 2011.2
Indonesia	ID	1990.1 – 2011.2
Ireland	IR	1960.1 – 2011.2
Israel	IS	1995.1 – 2011.2
Italy	IT	1960.1 – 2011.2
Japan	JP	1960.1 – 2011.2
Luxembourg	LX	1995.1 – 2011.2
Mexico	MX	1960.1 – 2011.2
Netherlands	NL	1977.1 – 2011.2
Austria	OE	1960.1 – 2011.2
Portugal	PT	1960.1 – 2011.2
Russian Federation	RS	2003.1 – 2011.2
South Africa	SA	1960.1 – 2011.2
Sweden	SD	1960.1 – 2011.2
Slovenia	SJ	1996.1 – 2011.2
Switzerland	SW	1960.1 – 2011.2
Turkey	TK	1998.1 – 2011.2
United Kingdom	UK	1955.1 – 2011.2
United States	US	1950.1 – 2011.2

Notes: sources, OECD, Datastream and National Statistics Institutions. The series employed is the Gross Domestic Product, expenditure approach, volume estimates in millions of national currency, quarterly and seasonally adjusted.

A careful analysis of methodological coherence has been carried out. We have proceeded as follows. First, we estimate an autoregressive equation AR(1) for each series and carry out the Quandt-Andrews stability test, both on the constant and the autoregressive parameter, identifying the position of the most likely break data and estimating its significance. Second, we estimate ARCH models and analyze the path of the conditional variance. Finally, when we identify significant breaks coinciding with methodological changes, we keep only those that show a match between national sources and the OECD database. For some countries the sample size is too short to make inference or detect properly turning points and have been removed. These countries are IC, KO, NO, NZ, PQ and SX.

TABLE A.2
CREDIT DATA

COUNTRY	ACRONYM	DOMESTIC CREDIT	Nominal GDP
Argentina	AG	1960.4 – 2011.3	1993.1 – 2011.2
Australia	AU	1957.1 – 2011.3	1959.3 – 2011.2
Germany	BD	1970.1 – 2011.2	1960.1 – 2011.2
Belgium	BG	1970.1 – 2011.2	1980.1 – 2011.2
Brazil	BR	1959.4 – 2011.2	1990.1 – 2011.2
Chile	CL	1967.1 – 2011.2	1996.1 – 2011.2
Canada	CN	1957.1 – 2008.4	1957.1 – 2011.2
Czech Republic	CZ	1993.1 – 2011.3	1993.1 – 2011.2
Denmark	DK	1970.1 – 2011.3	1977.1 – 2011.2
Estonia	EO	1991.4 – 2010.4	1993.1 – 2011.2
Spain	ES	1972.1 – 2011.2	1970.1 – 2011.2
Finland	FN	1970.1 – 2011.2	1970.1 – 2011.2
France	FR	1970.1 – 2011.2	1965.1 – 2011.2
Greece	GR	1970.1 – 2011.2	2000.1 – 2011.2
Hungary	HN	1982.4 – 2011.2	1995.1 – 2011.2
Indonesia	ID	1968.1 – 2011.3	1990.1 – 2011.2
Ireland	IR	1970.1 – 2011.2	1997.1 – 2011.2
Israel	IS	1957.1 – 2011.3	1971.1 – 2011.2
Italy	IT	1970.1 – 2011.3	1960.1 – 2011.2
Japan	JP	1957.1 – 2011.2	1957.1 – 2011.2
Luxembourg	LX	1970.1 – 2011.3	1999.1 – 2011.2
Mexico	MX	1957.1 – 2011.3	1981.1 – 2011.2
Netherlands	NL	1970.1 – 2011.3	1977.1 – 2011.2
Austria	OE	1970.1 – 2011.3	1964.1 – 2011.2
Portugal	PT	1970.1 – 2011.3	1977.1 – 2011.2
Russian Federation	RS	1993.4 – 2011.3	1994.1 – 2011.2
South Africa	SA	1971.2 – 2011.2	1960.1 – 2011.2
Sweden	SD	1969.4 – 2011.3	1980.1 – 2011.2
Slovenia	SJ	1991.4 – 2011.3	1995.1 – 2011.2
Switzerland	SW	1957.1 – 2011.2	1970.1 – 2011.2
Turkey	TK	1959.2 – 2011.2	1987.1 – 2011.2
United Kingdom	UK	1959.1 – 2011.3	1957.1 – 2011.2
United States	US	1957.1 – 2011.3	1957.1 – 2011.2

Notes: sources, International Monetary Fund, Financial Statistics, IFS.

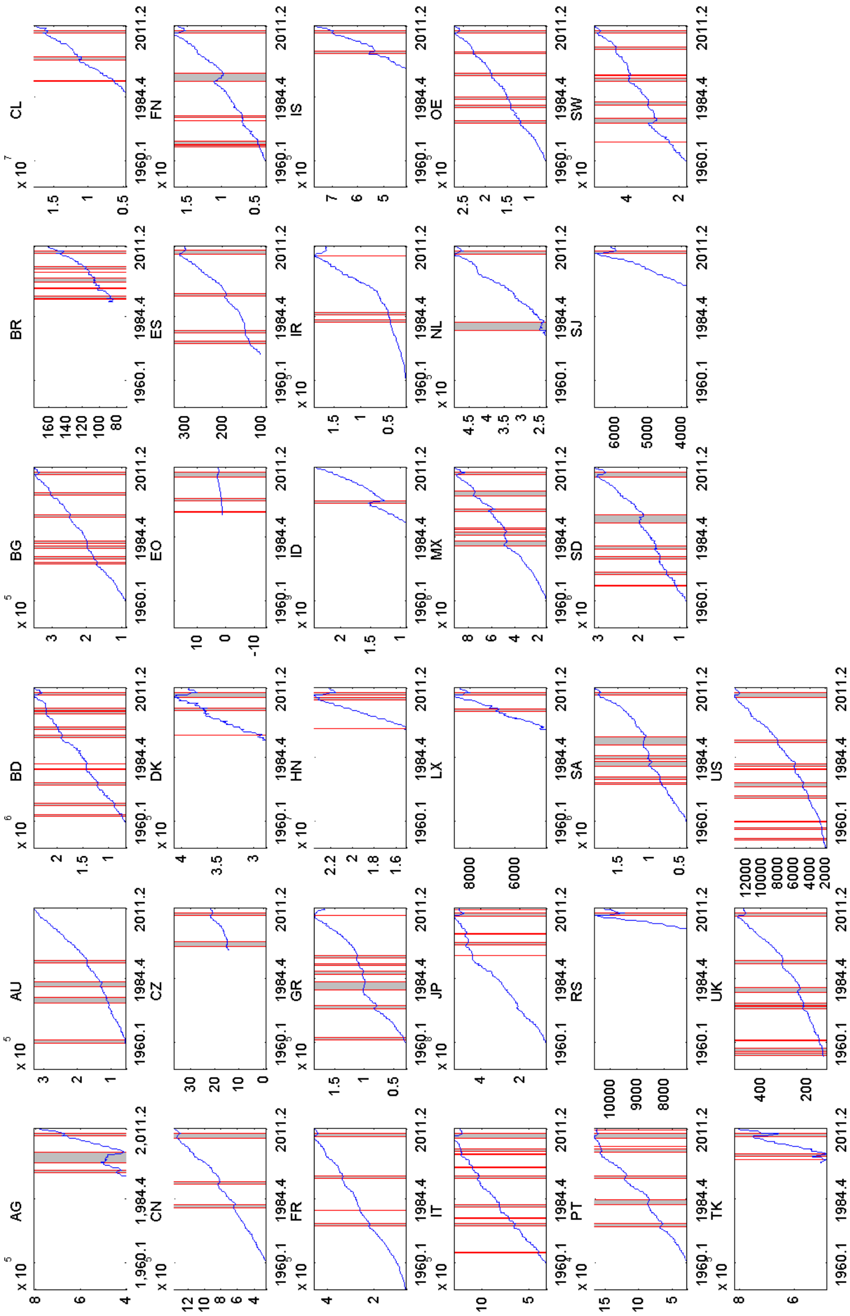

FIGURE A1. Bry-Boschan cycle dating and level of GDP for 33 OECD countries

Appendix 2. Capturing co-movements across countries

In order to properly address the presence of co-movements in the global model we have pursued several avenues. First, we have introduced a new ingredient into our model: the dependence of each country's economic cycle on what happens in the rest of the world (W_t). To do that, we follow a two-step process. In the first step, we estimate the global model and, with this estimation, we construct the probability of recession in the world by averaging in every period of the country probabilities obtained from this global model (for every period we have 30 countries). Second, we enlarge the global model by introducing the probability of being in a recession in the world in a time-varying transition probability (TVTP) Markov switching model (Filardo 1994), where $p_t = p + \delta_1 W_t$ and $q_t = q + \delta_2 W_t$.

The results show that the probability of a recession in the world economy has a negative influence on p and a positive one on q, and is significant in both cases. That is, the probability of remaining in expansion decreases, and that of being in recession increases, when the rest of the world is in recession[29]. Even though the coefficients are significant, qualitatively they are not very different from the global model that does not contain the world economy. The correlation between the probabilities of recession in these two specifications is 0.96. An additional drawback of this specification is that we are contemporaneously including the world economy and, consequently, the model has a limited forecasting ability. In order to address this point, we estimate a model that contains the state of the economy in the world in period $t-1$ obtaining non-significant and wrongly-signed coefficients. It seems that the possibilities of introducing comovements with this approach are limited.

But we are aware that co-movements between countries might act in other ways. In order to properly address the effect of co-movements in the model, we need to study the effect of cross-correlations between countries in the estimated parameters. If the effect is important, a multivariate estimation or a panel estimation that takes cross-correlation into account would be more suitable. But co-movements might be linear or non linear and disentangling the source of co-movements might have important implications in the estimation of the model. Although a proper analysis in a general specification lies outside the objectives of this paper, the nature of the

[29] We have refined this estimation with an iterative process after we estimate the second step. The iteration consists of re-estimating the model using the probabilities obtained in the second step as W_t and keep redoing the estimation until we reach convergence in W_t.

results can be obtained from the following simulation exercise. Suppose that two countries have the following DGP:

$$\begin{aligned} &\text{country 1:} \quad && y_{1t} = \mu_{s_{1t}} + \varepsilon_{1t} \; ; \varepsilon_{1t} = u_t + \zeta_{1t} \\ &\text{country 2:} \quad && y_{2t} = \mu_{s_{2t}} + \varepsilon_{2t} \; ; \varepsilon_{2t} = \rho u_t + \zeta_{2t} \end{aligned} \tag{12}$$

where s_{it} represents the state at time t of country i that is driven by a transition matrix with probability p, q[30], for expansions and recessions, respectively. Notice that both countries have a common shock, u_t, which is correlated between the two countries, and an idiosyncratic shock, and both are assumed to be mutually independent, zero-mean $i.i.d.$ processes. As can be seen, these countries co-move because they have a source of linear co-movements, the shock u_t which is common to both countries. But in addition to this source of co-movements, the countries could move together because their non linear component is also common. So, we now generate three types of series depending on whether the two countries share the state, do not share it, or do so partially :

1. share states: $s_{1t} = s_{2t}$ $\forall$ t
2. do not share states: s_{1t} independent of s_{2t}
3. share states partially: $s_{1t} = s_{2t}$ $\forall$ t=1:T/2 and s_{1t} independent of s_{2t} $\forall$ t=T/2+1:T

where T is the number of simulated observations.

We have estimated the three types of series with four different methods: a) individually country by country with a univariate MS model; b) jointly with a univariate MS model as in the "global model" explained before; c) with a bivariate model as if both countries share states (just one MS model describes the behavior of both countries); and, finally, d) with a bivariate model as if both countries do not share states (two hidden independent Markov processes). Results in Table A2 show that, when the countries share states, the univariate model both individually or jointly, performs similarly, and the improvement is small when we apply a bivariate estimation assuming the correct DGP (model c). However, if we use a bivariate model

[30] We assume that the p and q are the same for both countries in order to relate our results with the previous evidence that there are not such great differences across countries.

that supposes that countries do not share states (model d), the results worsen dramatically. The intuition is that the model *d* captures the non linear co-movement in the linear co-movements, implying a bias in the estimation coefficient that reduces the good fit of the dynamics of the MS process. Analogously, if the process does not share states, the univariate model estimates the parameters accurately and there is no important difference with respect to the bivariate model that estimates the two countries separately (model d) while it improves dramatically with respect to the model that, misleadingly, considers that the two countries share the non linear process (model *c*). Models *a* and *b* are robust to possible mispecifications of the degree of common non linearity. It is also important to note that models *a* and *b* perform similarly because the improvement from estimating the global model comes from the huge increase in the number of observations. Here we are considering only two countries, therefore, the increase in the number of observations is very limited. Finally, if the countries partially share states, we obtain intermediate results and the same conclusion. To sum up, the bivariate model works very well if we know the true characteristics of the data or if we establish them correctly in our Bayesian priors, but the univariate model yields very similar results even without knowing the true DGP. Finally, the degree of cross-correlation does not have a very important influence although the estimation problems are greater, the greater the value of ρ.

TABLE A2

ANALYSIS OF CROSS-CORRELATIONS

ρ	0.1	0.5	0.9
DGP: SHARE STATES			
Univariate MS, two countries separately	0.0853	0.0933	0.1123
Univariate MS, two countries jointly	0.0798	0.0877	0.1044
Bivariate MS, supposing that they share states	0.0455	0.0703	0.0886
Bivariate MS, supposing that they do not share states	0.1325	0.2101	0.2365
DGP: DO NOT SHARE STATES			
Univariate MS, two countries separately	0.0843	0.0935	0.1117
Univariate MS, two countries jointly	0.0795	0.0868	0.1020
Bivariate MS, supposing that they share states	0.2171	0.2312	0.2353
Bivariate MS, supposing that they do not share states	0.0826	0.0801	0.0760
DGP: SHARE STATES PARTIALLY			
Univariate MS, two countries separately	0.1502	0.1528	0.1506
Univariate MS, two countries jointly	0.1446	0.1469	0.1533
Bivariate MS, supposing that they share states	0.1310	0.1547	0.1693
Bivariate MS, supposing that they do not share states	0.0888	0.1035	0.1129

Notes: QPS of the difference between BB states and MS probabilities.

From this exercise, we can conclude that, even though the topic requires more research to generalize the results to *N* countries the gains from estimating a multivariate model are, at first sight, very limited. In general, the possible misspecification of the multivariate model, in the absence of proper priors, could lead to a massive loss of fit in the model. The results of the ”global model” proposed before are more robust to this kind of misspecifications.