The failure to predict the Great Recession. A view through the role of credit

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Abstract
Much has been written about why economists failed to predict the latest crisis. Reading the literature, it seems that this crisis was so obvious that economists must have been blind not to see it coming. We approach this failure by looking at one of the key variables in this analysis, the evolution of credit. We compare the conclusions reached in the recent literature with those that could have been drawn from an ex ante analysis. We show that the effect of credit on the business cycle can not be exploited from a policymaker's point of view. (JEL: C22, E32)

1. Introduction

A great deal has been written about the predictability of the latest recession. Given the financial origin of the recent downturn, interest in the topic of financial variables and business cycles has been rekindled. A broad and basically empirical body of literature has looked back at historical records and focused on documenting the timing of financial crises, establishing their typology and detecting the differences across them. Two important comprehensive attempts are Reinhart and Rogoff (2009), who build a massive database that encompasses the entire world across eight centuries, and Laeven and Valencia (2008, 2010), who provide data on the starting dates and characteristics of

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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, that the latest recession, often called 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 highlight 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. For example, Gourinchas and Obsfeld (2012) classify financial crises into different types by using several historical databases and analyze how key economic variables -especially credit- 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) and they find that the duration and amplitude of recessions and recoveries tend to be influenced by the strength and intensity of financial crises. The International Monetary Fund (2009) presents a compendium of most of these previous results.

Another set of papers tries to find these empirical regularities using longer historical datasets. This branch of literature includes Schularick and Taylor (2012) who 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. (2011, 2013) with different goals. Jorda et al. (2011) replicate the results of Schularick and Taylor (2012) and introduce external imbalances, concluding that credit growth emerges as the single best predictor of financial crises, and Jorda et al. (2013) detect the turning points and look at the behavior of real and financial aggregates across business cycle episodes. Their results show that credit booms tend to be followed by deeper recessions and sluggish recoveries.

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 fuels the expansion phase becomes the trigger for a financial crisis and, therefore, for a recession[1]. A common finding is that downturns associated with financial crashes are deeper and their recoveries slower.

These results have dramatically changed the way in which monetary policy is conducted because they all indicate that price stability does not guarantee macroeconomic stability and that monetary policy should coordinate with macroprudential policy to control, not only prices, but other financial variables, particularly, the evolution of credit. The combination of these two policies, by controlling financial imbalances, would lead to a new objective, financial stability (IMF 2013 and FSB, IMF and BIS 2011). In fact, according to the IMF, (IMF 2013), effective macroprudential policies (which include a range of constraints on different variables, including credit) should contain risks ex ante and help build buffers to absorb shocks ex post.

This last sentence is key. The search for ex ante risks has created a flourishing literature that tries to identify early warning indicators of financial and real crises (see, for example, Babecky et al 2012, Frankel and Saravelos, 2010 or the summary of the extensive work of Borio at the BIS, Borio 2012). These efforts were embodied in the IMF-FSB vulnerability exercise for advanced economies whose conclusions are included in the IMF (2010) official guidelines. However, all the previously-quoted empirical literature considers that financial crises or recessions are known a priori, 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 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 accumulate during expansions periods, the interpretation of the empirical findings is problematic 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"[2]. However, during long periods of expansion, credit to GDP growth is high and there is no recession. Moreover, 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 to predict the turning points. In medical terminology, the existing literature is more interested in the "anatomy" of financial crises, after they have occurred, than in "clinical medicine", that is,

1. Reinhart and Reinhart (2011) stress that this argument is especially important for the decade of prosperity prior to the crash of 2008.

2. Viñals (2012) quoting the Global Financial Stability Report, IMF, September 2011

diagnosis from the symptoms. But both perspectives are necessary to practice good medicine. Therefore, although the previous literature has 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. To be able to address risk "ex ante", we have to understand the dynamics of the financial variables in real time without forgetting the uncertainty surrounding turning points.

The key point of our proposal is to consider the cyclical phases and, especially, recessions in an environment of real time 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 continues to generate 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 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 different steps. First, we show the limitations of the existing literature when trying to answer these questions (Section 2). Second, we show the need to use techniques that address, in real time, the uncertainty about the state of the economy. We use the univariate Markov Switching models proposed by Hamilton (1989) extended to take into account the cross-sectional dimension of our dataset . We show that this approach is legitimate, notably reduces the uncertainty associated with the univariate estimation of recession phases and improves forecasting ability in real time. Having obtained a model that it is reliable and describes, in real time and with reduced uncertainty, the probability of recession, we introduce different transformations of credit and evaluate, in real time, how credit modifies the probability of recessions and the characteristics of future recession periods (Section 3).

Our results can be summarized as follows. Even though 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, these results are only in-sample. There is no significant gain in forecasting turning points or business cycle characteristics as a consequence of introducing credit because the close relation between credit and growth is basically driven by the Great Recession.

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[3]. After reading the literature, he/she will reach the conclusion that credit to GDP growth is a particularly reliable indicator of recessions. This conclusion is reached in the literature by using different transformations of the credit to GDP ratio, levels, variations or variations divided by expansion durations. For example, Gourinchas and Obsfeld (2012) and Kamisnky and Reinhart (1999) use the series in levels. Figure 1 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 it 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 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 each 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. (2011, 2013) 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 credit to GDP ratio (IMF 2009; Jorda et al. 2011). However, this variable still has a trend. To test for this trending behavior, we repeat our previous analyses using the variation in the ratio. The results, for the US case, the 39 countries case and the Jorda et al. (2011) 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 than the other (GDP), which seems to be a stylized fact in the data.

3. This is particularly relevant now because the IMF is currently formulating this question for the case of the rapid credit growth in Latin American countries. See Hansen and Sulla (2013).

Finally, some other papers construct different transformations of this ratio, such as, for example, credit intensity (Jorda et al. 2013). This variable is defined as the cumulative difference between credit growth and GDP growth normalized by the duration of the expansion. However, as in the two previous cases, this variable has a significant trend. The results are shown in the third panel of Table 1. Credit intensity still presents a positive and significant expansion-related trend[4],[5].

This trending behaviour is not without its effects on the econometric methodolology generally used in the literature, particularly with respect to the interpretation of the results, because we could infer predictive power when we are just capturing that credit to GDP (or its variation) is usually high at the end of expansion periods. In other words, what we are really capturing is that the mean of the growing variable is higher at the end than at the beginning of each expansion -fundamentally a descriptive result- without having any influence on the predictability of the next turning point. 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 hypothetical recession, but with this decision they could shorten a healthy expansion period.

In addition to the 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[6]. A fall in credit in period "$t, t+1....t+k$" 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

4. For completeness, we also analyze real credit growth, which is the variable chosen by Schularick and Taylor (2012). For their sample, this variable also presents a significant trend (coefficient 0.045 and t-ratio 6.77). For our sample of 39 countries, the trend is also positive and significant (coefficient 0.026 with t-ratio of 6.58).

5. Given that either the credit to GDP ratio or the different transformations of Credit show significant trends during expansion periods, we will concentrate our analysis on the level of the credit to GDP ratio and will present a robustness analysis using other transformations in the online Appendix. In this way, although the variable that we have chosen brings our paper closer to Gourinchas and Obsfeld (2012) than to other papers in the literature, our results can be extended to all the other specifications [Jorda et al. (2011, 2013) and Schularick and Taylor (2012)].

6. Even if credit were not considered in the definition of recessions, it is an endogenous variable and, therefore, correlated to GDP and its turning points. The endogeneity of credit is not only demonstrated in the theory. Thanks to the suggestion of one of the referees, we have obtained empirical evidence that confirms this fact, derived from a VAR specification. The latter clearly rejects that credit Granger causes GDP, but not the inverse. The results are displayed in the online appendix, Section A.3.

variable "future recession in the next k periods" as before, "z_t", and we run the following regression:

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

$E(\varepsilon_t, credit_t) \neq 0$, because "$z_t$" is defined by looking at the evolution of "$credit_{t+1....t+k}$" 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 a 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 (2012), 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 (2012) 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.

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 so, we are going to analyze the forecasting power of the level of credit to GDP (or other transformations of credit) 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 current information. But first, we need a formal definition of turning point and a description of the characteristics of the cycle.

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

7. Jorda et al. (2013) make the point that excess credit is a problem in all business cycles, not just in financial crises.

sample of reference is 1950.1 to 2011.2 for 39 OECD countries although there are missing data for some of them. Due to clear methodological changes in the data or samples that are too short, we have had to discard six countries. The final selection of countries is: Argentina (AG), Australia (AU), Germany (BD), Belgium (BG), Brazil (BR), Chile (CL), Canada (CN), Czech Republic (CZ), Denmark (DK), Estonia (EO), Spain (ES), Finland (FN), France (FR), Greece (GR), Hungary (HN), Indonesia (ID), Ireland (IR), Israel (IS), Italy (IT), Japan (JP), Luxembourg (LX), Mexico (MX), Netherlands (NL), Austria (OE), Portugal (PT), Russian Federation (RS), South Africa (SA), Sweden (SD), Slovenia (SJ), Switzerland (SW), Turkey (TK), United Kingdom (UK) and United States (US). The online Appendix (Section A.4)presents details on the sample period for each country.

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). 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

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 cycles, it has the inconvenience that it is mainly a descriptive method only useful for the past. 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 in each country[8]:

$$dy_t = \mu_{S_t} + \varepsilon_t \tag{3}$$

where dy_t is the growth rate of GDP in each country, μ_{S_t} is the vector of Markov switching intercepts and ε_t ∼N(0, σ). To complete the statistical specification, it is standard to assume that these varying parameters depend on an unobservable state variable, S_t, 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. 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 for each country with a MLE algorithm are displayed in Table A0.1 of the online Appendix. 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, respectively. However, and as happened in the BB case, the results show significant heterogeneity. Furthermore, the standard errors associated with the probability of recession are usually high, which results in 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 FR, 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[9]. 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. In this context, to expand the model to incorporate credit and to test the significance of the estimated credit parameters will always lead 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.

3.2.2. Global model estimation.

8. Our formulation of the MS model implies stationarity. The application of a battery of unit root tests confirms the result that GDP series are I(1) in log levels.

9. 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.

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 and, in particular, the transition probabilities, which dominate the business cycle characteristics, are constant for the whole sample. We assume this even though it is clear 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 this 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, as 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 (8 quarters) and check the characteristics of the recessions and expansions that appear for all the 33 countries in each of those 30 intervals[10]. For example, the first interval represents the period 1950.1-1952.1 and we calculate the characteristics of the recessions during that period; interval 2 collects the recessions from 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. In order to formally check 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

10. We use 30 intervals in order to match the number of countries as closely as possible.

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: duration, amplitude, cumulation and excess. The results, displayed in Table 2, show that we fail to reject that all the countries come from the same population for all the characteristics at 5% significance, but we reject this hypothesis in the time series dimension. For example, for duration, grouped by country, we can not reject 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.

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 neighbouring clusters. After that, we analyze the concentration of periods and countries in each cluster using the Herfhindal index. The results are displayed in table A0.2 of the online Appendix. 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. In other words, 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 do not worry about mixing heterogeneous features, there should be no problem in estimating a panel 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 the GDP growth of country c in period t as $dy_{t,c}$, T_c being its sample size. Then, our left-hand-side variable is

$$dY = \{dy_{t,c}\}_{t=1:T_c;\ c=1:N} = \{dy_{11}, ..., dy_{T_1 1}, ..., dy_{1c}, ..., dy_{T_c c}, ..., dy_{1N,...}, dy_{T_N N}\} \tag{4}$$

where T_c is the sample size of country c and N is the number of countries. For simplicity, we standardize each country, otherwise we would have to remove the variation in mean and growth rate across countries, having to deal with fixed effects and random effects to capture the specificities of each country. Then, we obtain

$$d\widetilde{Y} = \{d\widetilde{y}_{t,c}\}_{t=1:T_c;\ c=1:N} = \{d\widetilde{y}_{11}, ..., d\widetilde{y}_{T_1 1}, ..., d\widetilde{y}_{1c}, ..., d\widetilde{y}_{T_c c}, ..., d\widetilde{y}_{1N,...}, d\widetilde{y}_{T_N N}\} \tag{5}$$

where $\{d\widetilde{y}_{t,c}\} = \{dy_{t,c}\}$ with the mean and standard deviation of dY.

Model estimation. We estimate the panel $(d\widetilde{Y})$ as defined in (3) with a MS model with two states. So, the estimated model is:

$$\widetilde{dy}_{t,c} = \mu_{S_{t,c}} + \varepsilon_{t,c} \tag{6}$$

and the normalization of the series allows us to assume that $\mu_1 = \mu_{1c}$ and $\mu_2 = \mu_{2c}$ $\forall c$. In addition, in accordance with the previous discussion, we can impose that $p = p_c$ and $q = q_c$ $\forall c$.

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 details of parameter estimates are displayed in the first line of Table 3. It is noteworthy that the standard errors associated with the probability of recession are considerably lower than the ones of the recessions in each country. The data and probabilities of this global model are displayed in figure A0.1 of the online Appendix. Obviously, in this figure, it is difficult to distinguish each country because we are plotting around 5,000 observations corresponding to all the countries, one after the other with the vertical lines separating one country from 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 (the average correlation is 0.8). 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 corresponds, for each country "i", to the parameter distribution of the model estimated for all the countries excluding country "i".

Furthermore, we compare the turning points computed with the BB algorithm, which 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)[11] fall dramatically when we use the panel estimation. 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 global model, it is 0.08. The intuition of why there is such a strong reduction in the QPS can be seen by analyzing the case of FR. Figure 2, top panel, plots the recession probabilities obtained with the global model and the recession probabilities obtained by estimating the country model for FR. 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, but the priors that come from the rest of the world help to fit the French recession dates better.

11. To compute them, we use the definition of Quadratic Probability Score (QPS) of Diebold and Rudebusch (1990), $QPS = 1/T \sum_{t=1}^{T} (Pt - BBt)^2$, which ranges from 0 to 1, with a score of 0 corresponding to perfect 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).

However, in the case of US, (Figure 2, bottom panel) the difference is not so important and the country and global model probabilities of recessions are highly correlated.

In short, we have shown that we can mix countries and take advantage of the cross-sectional dimension and, so, we can use a panel of around 5,000 observations. The estimation of recession probabilities leads to similar results to those obtained with BB methods giving us 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. In order to capture this, we enlarge (6) to incorporate the possibility of co-movements in the idiosyncratic shocks. Following Pesaran (2006), we capture these common shocks using the principal components of the idiosyncratic residuals of the model. Given that we have an unbalanced dataset, we use the method of Stock and Watson (2002) to fill in the missing variables. Therefore, the estimated model is:

$$d\widetilde{y}_{t,c} = \mu_{S_{t,c}} + \lambda F_t + \varepsilon_{t,c} \tag{7}$$

The estimated λ is positive and significant. However, the estimated probabilities of recession and expansion are very similar to those estimated in (6). The correlation between these two probabilities is higher than 0.82. Therefore, the global model proposed in (6) stands as a robust framework even in the presence of 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 each period until the last but 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 $P_{t,c}$ the conditional probability at time t of being in a recession, the probability of being in a recession at time $t+1$ is $P_{t+1c} = (1-p_t)(1-P_{t,c}) + q_t P(_{t,c})$ 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 when 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)[12]. 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 recession periods. Now, it is time to allow for the possibility of credit to modify this 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 ($CR_{t,c}$) for time t and country c. This variable has been used in the most relevant empirical literature that studies financial crises [Gourinchas and Obstfeld (2012); 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 taken from the International Monetary Fund (International Financial Statistics, IFS) and require some adjustment such as removing seasonality (in nominal GDP), matching exchange rates and homogenizing units [13]. As we mentioned before, we present the results of the analysis using the level of credit to GDP ratio as the previously quoted authors do. However, we also estimate all the results with the variation in credit to GDP ratio, and all the other specifications proposed

12. We have also applied the Giacomini and White (2006) test for unconditional predictive ability using a rolling procedure and the conclusions are similar.

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

in the literature. All the results of the robustness analysis are in the online appendix.

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. In parallel, we have built the panel for domestic credit, called $CR_{t,c}$, where t=$1, ..., T_c$ and $c = 1, ..., N$.

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:

$$\begin{aligned} d\widetilde{Y}_{t,c} &= \mu_{S_{t,c},t} + \varepsilon_{t,c} \\ \mu_{1t,c} &= \mu_1 + \alpha_1 * CR_{t-1,c} \text{ for state 1 } \forall c \\ \mu_{2t,c} &= \mu_2 + \alpha_2 * CR_{t-1,c} \text{ for state 2 } \forall c \end{aligned} \tag{8}$$

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

$$\begin{aligned} p_{t,c} &= p + \delta_1 * CR_{t-1,c} \text{ for state 1 } \forall c \\ q_{t,c} &= q + \delta_2 * CR_{t-1,c} \text{ for state 2 } \forall c \end{aligned} \tag{9}$$

Notice that we include the credit ratio with a lag in order to use this information for forecasting at time t. Table 3 (second row) summarizes the results of estimating the baseline model without introducing credit. The differences between the results of the first and the second row are due to the fact that the second row is the estimation of the baseline model for the available sample when we have credit. The other rows of Table 3 present the results for the model with time-varying means, the model with time-varying transition probabilities and the model that includes both time-varying means and probabilities. 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 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 only marginally 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. We do not consider the model that includes the credit to

GDP ratio affecting both the mean of the states and the probabilities because the model presents potential identification problems when trying to estimate simultaneously the effects of the same variable on both the mean and the probabilities.[14] In terms of the in-sample analysis, the results of fitting the recession periods show that the inclusion of the financial variable does not affect 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.

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 probability of being in recession in each period t,

$$E(\mu_2) = \sum_{c=1}^{N}\sum_{t=1}^{T_c} \mu_{2t,c} P(rec_{t,c}) / \sum_{c=1}^{N}\sum_{t=1}^{T_c} P(rec_{t,c})$$

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:

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

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

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

$$E(D) = \sum_{c=1}^{N}\sum_{t=1}^{T_c} d_{t,c} P(rec_{t,c}) / \sum_{c=1}^{N}\sum_{t=1}^{T_c} P(rec_{t,c}), \text{ where } d_{t,c} = 1/(1-q_{t,c})$$

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

14. This lack of identification results on in increase in the standard deviation of the coefficients of the model with time varying mean and probabilities. That implies that we never get significant coefficients simultaneously in the parameters of the mean and the probabilities. In addition, in some specifications we observe a lack of robustness in some of the coefficients with respect to the ones estimated in the models where only the mean or the probabilities change (see table A1.7 of the appendix, for example).

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

where $P(rec_{t,c})$ is the probability of being in recession at each time t in country c, T_c is the sample size of country c and N the number of countries.

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 A0.3 in the online Appendix).

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 3 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 reaches maximum values above 2, the amplitude of the recession is -6.7, which is an increase of almost 50% over the average value of -4.5. Similarly, the duration may be up to 4.5 quarters 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.

Therefore, this section reconciles our results with the standard results in the recent literature. It seems that credit affects the probability of being in recession. The 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 we need to answer whether the credit to GDP ratio has predictive power on business cycle turning points or characteristics.

3.3.2. Out-of-sample analysis. To see a 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 to what extent 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 focus on 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). We analyze the ability of these models to forecast both the probability of entering into recession and the business cycle characteristics. 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[15].

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. The Diebold and Mariano (1995) test shows that neither the model with probability that considers 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 Table 4. 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. We repeat the exercise concentrating on the predictive power of the different models in the first two periods of the turning points. The GM presents similar FQPS to the GM_credit_μ and the GM_credit_prob models, as presented in Table A0.4 of the online appendix. This Table also presents the forecast of the features of the recessions with parameters estimated at time t. The main conclusion is that there are no important differences in the forecasting ability of the global models.

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 all the series, following the BB chronology, and we have studied several indicators, which are shown in the Table A0.4 of the online Appendix. Each of the rows of this table display the results of forecasting recession features at the beginning of the recession for each model. For all the characteristics, duration, amplitude and cumulation, the GM presents smaller forecasted MSE compared with the forecasts made by the three models in the first quarter of a 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

15. 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.

credit in period t nor forecast the characteristics of forthcoming recessions with this variable[16].

Given the importance of the previous result, we need to point out that this poor out-of-sample performance is not a consequence of using the MS methodology. In fact, we replicate the same out-of-sample exercise as we have done with the MS model but employing a logit specification, which has been the standard method used by previous papers. As expected, the credit variable presents in-sample a positive and significant coefficient, the estimated value being 0.25 with a p-value of 0.00. However, as in the MS models, the out-of-sample performance of the logit specification is poor. Actually, the results are poorer than those estimated for the MS. The QPS and FQPS of the logit and the MS are displayed in Table 5. As can be seen, both in-sample and out-of-sample, the results of the logit specification present higher QPS and FQPS than the MS specification with and without including credit. These differences in favor of the MS models are statistically significant. Therefore, the poor out-of-sample performance is a characteristic of the data, not of the method used to transform the data into a forecasted probability of recession.

Finally, the online appendix includes different robustness analyses, using all the series proposed in the literature as alternatives to the level of credit to GDP ratio following Schularick and Taylor (2012) and Jorda et al (201, 2013). We use credit ratio growth, credit ratio only in developed countries, credit ratio growth only in developed countries, credit ratio 5-year moving average, credit ratio growth 5-year moving average, real credit growth, real credit growth 5-year moving average and the standardized credit to GDP ratio. We standardize credit even though the object of the paper is to capture the international path of credit/GDP ratio but not to build an index that moves between [0,1]. As can be seen in Tables A1.1 to A1.13 of the Section A.1 of the online appendix, our conclusions are robust to all specifications. We have also explored the interaction of credit with other variables such as stock returns and housing prices and repeated the exercise with debt service ratio instead of credit. The results (Tables A1.14 to A1.16) are also robust to this set up.

But, 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 only up to the beginning of the Great Recession. The first

16. We understand that not all crises have a financial origin and this 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 (2012). Our results displayed in the online appendix (Section A0.2), 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.

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 on which our analysis has focused in the previous section, the model with time-varying state means and the model with time-varying transition probabilities. The results are displayed in rows six and seven of Table 3.

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 until late 2008. 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 inferences about the future.

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. We only consider the effect of previous duration in the transition probability of recessions[17]. The expression of the probability of staying in recession is $q_{t,c} = q + \theta \sum_{i=1}^{d} P(rec_{t-i,c})$. We have considered a maximum value of d=8, based on the results obtained with the BB method.[18] We have also combined the mean time-varying model depending

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

18. 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.

on credit with the duration-dependence probability of being in recession [19]. The results of estimating the two models appear in lines 8 and 9 of Table 3. 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.

What is interesting about this specification is the out-of-sample performance. The results of the two-by-two formal statistical comparisons of the forecasting of turning points at time $t+1$ with information at time t by using the Diebold and Mariano test are presented in Table 4. The model that only contains the duration dependence is denoted by GM_dd. The model that contains duration-dependence and time-varying means 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.

This good out-of-sample performance of the GM_dd model also extends to the forecasting of the business cycle characteristics. The results are displayed in the online Appendix (Table A0.4). 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.

4. Conclusions

In this paper, we analyze why forecasting the Great Recession was a difficult task. We illustrate these difficulties by looking at one of the most cited and

19. The results of mixing duration-dependent probability models and time-varying transition probabilities with credit imply specification problems and unstable solutions.

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 mostly caused by the latest recession. The comparison of the forecast performance of models that include credit with other global models shows that there is no significant gain from 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 could shed some light on 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, either in an in-sample (previous to the crisis) or 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.

From this failure in forecasting the latest recession, by missing something (ex post) as obvious as the role of credit, we can conclude that, when validating the models for extreme events, theory should play a role that statistics might not be able to play because empirical evidence might arrive too late for predicting these events. However, from now on, with the evidence that we gather in the paper, we think that credit should be included as an early warning indicator and that any effort to enlarge dynamic general equilibrium models to include the financial accelerator, taking into account the forecasting ability of the business cycle characteristics as suggested in Pagan and Robinson (2014), should be welcomed.

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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, 2013)'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 a measure of credit (credit to GDP ratio, variation of credit ratio or credit intensity) 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, 2013)'s data, we have carried out a panel estimation.

Table 2. 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 parentheses. For periods, the sample has been split into 30 groups.

Table 3. Global model estimation.

μ_1	μ_2	σ^2	p	q	δ_1	δ_2	α_1	α_2	θ
MS Model with fixed means and probabilities (full sample)									
0.97	−1.46	1.09	0.97	0.65					
(0.019)	(0.122)	(0.025)	(0.001)	(0.035)					
MS Model with fixed means and probabilities (sample restricted to credit data)									
0.87	−1.84	1.01	0.97	0.60					
(0.019)	(0.112)	(0.026)	(0.001)	(0.037)					
MS Model with fixed probabilities and time-varying means depending on credit									
1.14	−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 depending on credit									
0.87	−1.84	1.01	0.97	0.50	−0.00	0.11			
(0.019)	(0.121)	(0.027)	(0.000)	(0.068)	(0.003)	(0.057)			
MS Model with time-varying means and probabilities depending on credit									
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)	(0.075)	(0.039)	(0.209)	
MS Model with fixed probabilities and time-varying means depending on credit (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 depending on credit (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 depending on credit									
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: First, we have estimated a MS model with 2 states and a constant variance for the global model where $\widetilde{dy}_{t,c} = \mu_1 + \varepsilon_{t,c}$ for state 1 and $\widetilde{dy}_{t,c} = \mu_2 + \varepsilon_{t,c}$ for state 2, $\widetilde{dy}_{t,c}$ being the log rate growth of GDP of country c in time t. Secondly, we have estimated a time-varying transition probability (TVTP) Markow switching model where $p_{t,c} = p + \delta_1 * CR_{t-1,c}$ and $q_{t,c} = q + \delta_1 * CR_{t-1,c}$ where CR is the ratio of credit to GDP and a model where CR affects the means of the two states, $\mu_{1t,c} = \mu_1 + \alpha_1 * CR_{t-1,c}$ and $\mu_{2t,c} = \mu_2 + \alpha_2 * CR_{t-1,c}$. In addition, a duration-dependence model has been estimated, where θ means the effect of the duration of the current recession. Standard errors in parentheses.

TABLE 4. Comparing forecasting of probability of recessions (Diebold and Mariano test)

	GM	GM_credit_mu	GM_credit_prob	GM_dd	GM_dd_credit_mu
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_m			FQPS1=0.1140 FQPS2=0.1168 DM_test=-0.7690 (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_m					

Notes: The first value corresponds with rows and the second with columns. The third values display the Diabold and Mariano test and its associated p-values of the null hypotheiss that the predictive performance of model in row and model in column is equal.

TABLE 5. Credit Performance with Logit Model.

	Logit	GM	GM_prob_credit
		In sample	
QPS	0.12	0.08	0.08
		Out-of-sample	
FQPS	0.14	0.11	0.12
DM test		5.80 (0.000)	4.31 (0.000)

Notes: FQPS of the difference between BB states and Logit and MS forecast probabilities. Diebold and Mariano test and p-values in parentheses for the null hypothesis that the predictive performances of GM models and logit are equal.

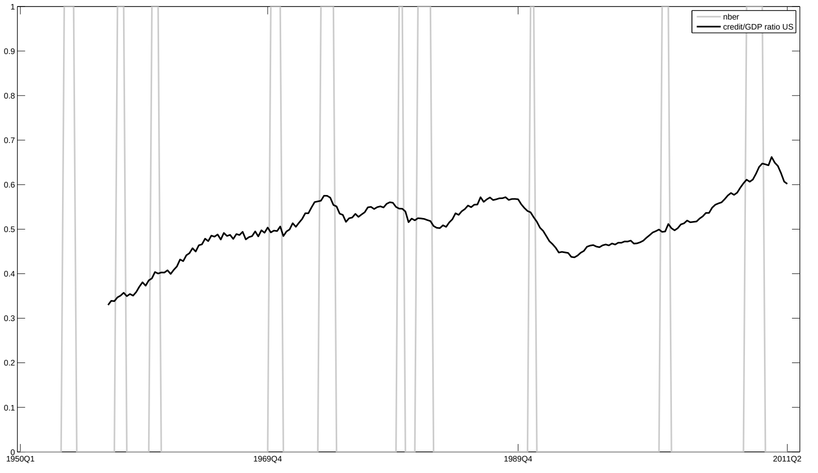
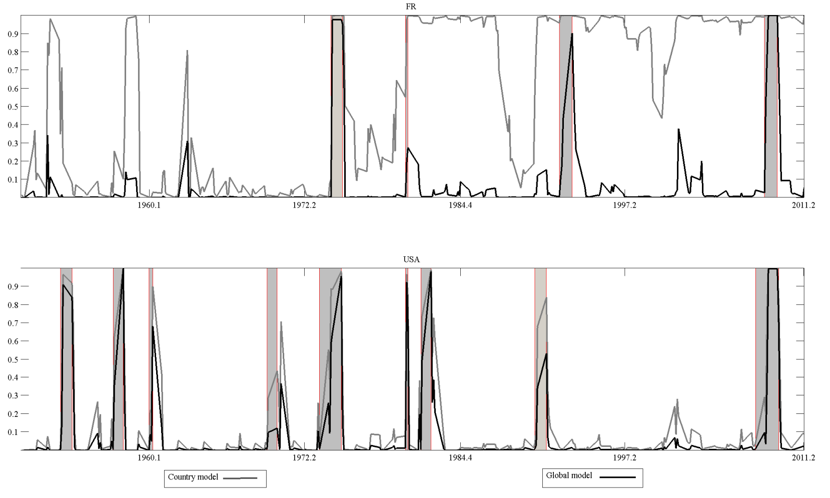
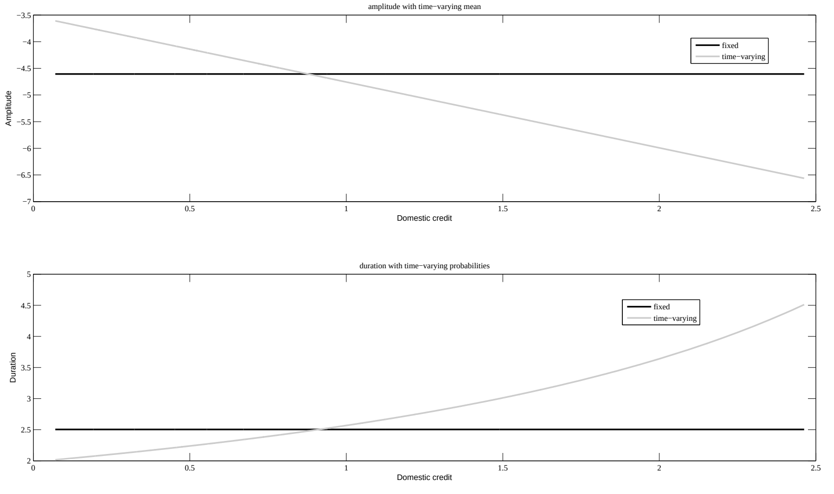


FIGURE 1. Trending expansion behavior of credit



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

FIGURE 2. Comparing recession probabilities in France and USA



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 3. Effects of extreme values of the Credit to GDP ratio on recessions characteristics