

**CREDIT CYCLES: EVIDENCE  
BASED ON A NON LINEAR MODEL  
FOR DEVELOPED COUNTRIES**

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# **CREDIT CYCLES: EVIDENCE BASED ON A NON-LINEAR MODEL FOR DEVELOPED COUNTRIES <sup>(\*)</sup> <sup>(\*\*)</sup>**

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## **Abstract**

We propose an econometric analysis of the evolution of bank credit to the private sector in order to describe credit cycles and identify phases of particularly low (or negative) credit growth such as those that typically accompany financial or banking crises. We use a sample of twelve developed countries, which improves the reliability of our estimation results and provides a global view of the situation of credit for developed countries. In our preferred specification, the credit cycle is characterized as a three-state Markov-switching model that identifies episodes of credit expansion, intermediate credit growth and subpar growth or credit crisis. This specification identifies six of the countries as having experienced period of credit adjustment after the beginning of the financial crisis in 2007 (Canada, Germany, Netherlands, Spain, Switzerland and US). By the end of the sample period, credit growth was still impaired in three of these countries (Germany and Spain in 2010:I; and United States in 2009:IV). The analysis also uncovers a systematic cyclical pattern in the bank lending sector of the group of advanced countries considered in our sample, which have experienced five episodes of synchronous restrictions in bank lending: 1974-75, 1980-82, 1991-93, 2001-02 and from 2008 to the end of the sample.

**Keywords:** Credit cycle, banking crisis, financial crisis, Markov, business cycle.

**JEL classification:** E44; E51; G01; G21.

## Resumen

En este estudio se propone un análisis econométrico de la evolución del crédito bancario al sector privado con el objetivo de describir los ciclos de crédito e identificar, por ejemplo, las fases de crecimiento anormalmente bajo, como las que suelen asociarse con episodios de crisis financiera o bancaria. En el trabajo se emplea una muestra de doce países desarrollados lo cual permite una visión global de la situación del crédito en las economías avanzadas y mejora las propiedades estadísticas de la estimación. Los resultados sugieren que la mejor descripción del ciclo de crédito se realizaría mediante un modelo de Markov de regímenes cambiantes que tuviese tres estados (expansión, crecimiento intermedio y contracción del crédito). Bajo esta especificación, seis países de la muestra se encontrarían en un episodio de ajuste o contracción del crecimiento del crédito tras el inicio de la crisis financiera en 2007 (Alemania, Canadá, España, Estados Unidos, Holanda y Suiza). Respecto al último período considerado, el crecimiento del crédito continuaría en ese estadio en tres de esos países (Alemania, España y Estados Unidos). Además, los resultados aportan evidencia sobre la existencia de un patrón cíclico sistemático en el crecimiento del crédito para el grupo de países considerado, identificando cinco episodios de restricciones sincronizadas en el crédito bancario: 1974-75, 1980-82, 1991-93, 2001-02 y desde 2008 al final de la muestra.

**Palabras claves:** Ciclo de crédito, crisis bancaria, crisis financiera, Markov, ciclo económico.

**Códigos JEL:** E44; E51; G01; G21.

# 1 Introduction

Real credit growth fluctuates over time, following a boom-bust pattern. There is a strand of the literature that has found evidence about the cyclical pattern of credit. For example, Schularick and Taylor (2009) suggest the existence of boom-bust episodes for the credit cycle, arguing that credit growth contains valuable information about the likelihood of future financial crises. Several empirical studies have centered on the identification of changes in bank credit allocation and episodes of severe restrictions in bank lending, sometimes called “credit crunches,” that coincide with banking crisis episodes. This strand of the literature is mostly based on case studies and econometric analysis are few. In this context, we propose a nonlinear model for the evolution of real credit growth as an attempt to achieve an objective identification of credit cycle dynamics. The main target of this paper is to describe credit cycles and identify phases of particularly low (or negative) credit growth such as those that typically accompany financial crises.

We model the evolution of the quarterly growth rate of real bank credit to the private sector as a Markov-switching process using the methodology proposed by Hamilton (1989) for a sample that includes the countries that the OECD describes as G10 plus Spain over the period 1960:I-2010:I. G10 countries in the OECD grouping are Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, United Kingdom and United States. In particular, credit dynamics are modeled as a combination of a country-specific component and a cyclical component following the multi-country approach proposed by Ceron and Suarez (2006). In this study we focus on the evolution of the cyclical component by specifying the non-linear structure over the standardized series of real credit growth. There are two advantages of using this multi-country approach: it provides a broad view of the situation of credit for these developed economies, and it helps to increase the reliability of the estimates for the parameters of the model (specially when the time series dimension of the panel may be too short, and the number of switches too small, compared to the average duration of credit phases<sup>1</sup>).

First, we propose the estimation of the model with two latent states in which the expected duration of credit crises as defined by this model and the mean growth rates obtained suggest

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<sup>1</sup> Estimation results evidence that the expected duration of each cyclical phase tends to last more than two years.



that the pattern that this model captures is more related to rather long phases of high and lows in real credit growth more than credit booms and busts. Following this reasoning, we consider the estimation of a restricted version of the model with two states, in which we impose the value of the mean growth rate for the credit crisis state in the estimation. This exercise represents an intermediate stage prior to the estimation of the model with three states, which is our preferred specification of the model. Finally, in order to filter out the effect of GDP growth on the credit cycle, we consider the estimation of the models with two and three states including lagged GDP growth as an explanatory variable for the mean growth rate of real credit growth.

After considering this range of models, we find that the credit cycle can be best described through a three-state Markov-switching model in which, as a matter of convention,  $s_{it} = 1$  identifies a “credit expansion” state,  $s_{it} = 2$  an “intermediate growth” state, and  $s_{it} = 3$  a “credit crisis” state. Credit crisis phases have a mean growth rate of  $-121.2\%$  of one standard deviation of the original series and they are found to be the least persistent state, with an expected duration of 7.4 quarters and an unconditional probability of 18.1%. Credit expansion phases have a mean growth rate of 80.8% and they last around 13.0 quarters with an unconditional probability of 37.1%. Intermediate growth phases have a mean growth rate of  $-18.5\%$  of one standard deviation of the original series with an expected duration of 7.4 quarters and a frequency of 44.8%.

With respect to the enlarged version of these models, that is, the one in which lagged GDP growth is included as an explanatory variable for the mean of real credit growth, the effect of this variable reflects a positive but quantitatively small effect of the evolution of real economic activity (as measured by GDP growth) on the developments in bank credit to the private sector.<sup>2</sup>

The preferred version of the model identifies six of the countries as having experienced a credit crisis episode after the beginning of the financial crisis in 2007 (Canada, Germany, Netherlands,

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<sup>2</sup>In an attempt to capture possible ruptures in the dynamics of both real credit growth and economic growth, as well as any possible feedback from credit growth to GDP growth, we tried an alternative specification in which we included GDP growth as a second endogenous variable in a vector autoregressive (VAR) context. It turned out that the results obtained from the estimation of the Markov-Switching vector autoregressive model (MS-VAR) relative to the identification of credit crisis phases were almost the same as in the univariate version. Because of the little contribution of GDP growth to disentangle credit crisis phases, and because the model was not able to improve the goodness-of-fit for real output growth relative to the univariate version proposed by other authors (in terms of the mean squared error obtained using each model), we decided to skip the details on the results obtained with this specification.



Spain, Switzerland and US). By the end of the sample period, three of these countries were still in a credit crisis episode (Germany and Spain in 2010:I; and United States in 2009:IV). Comparisons between the evolution of the smoothed probability of being in a credit crisis and the credit standards required by commercial banks suggest that the latter lead the credit cycle for the case of the United States (and also for the case of the Euro Area, although the result is much less definitive due to the heterogeneity present among euro area countries). This coincides with the results found with other methodologies (e.g., Lown and Morgan, 2006) about the validity of credit standard surveys as a form of leading indicators for the credit cycle.

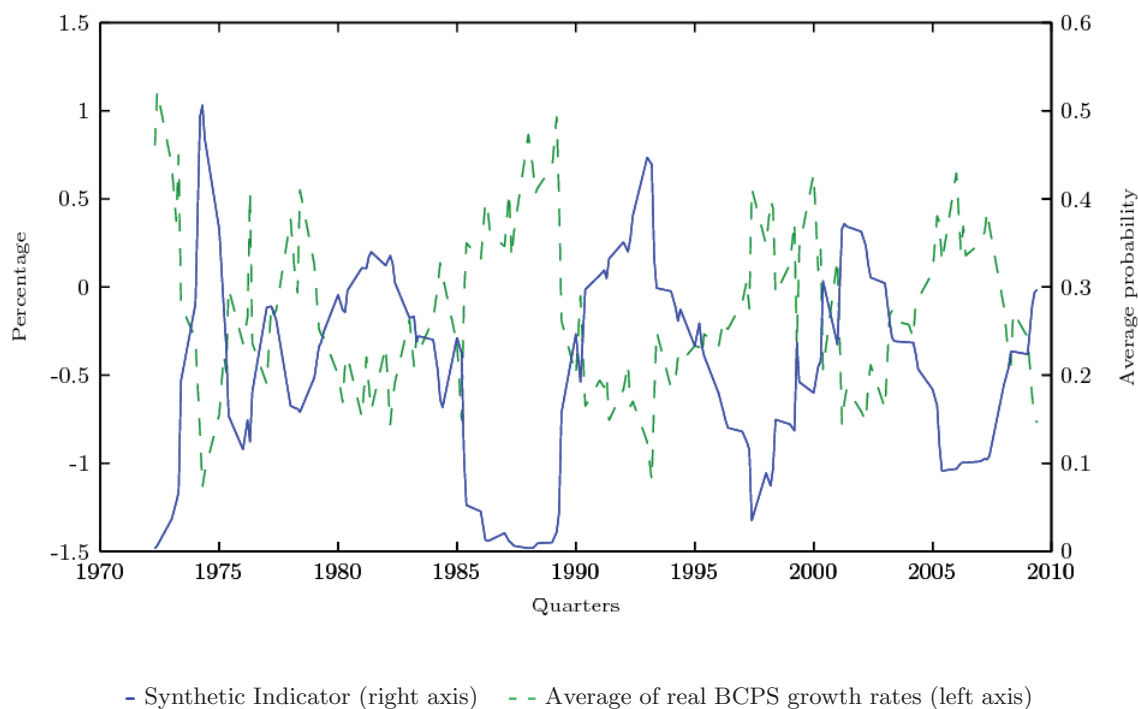
Our proposal helps to clarify the analysis of the situation of credit at the international level, since we are able to study the evolution of the probabilities of being in a credit crisis for all of the countries in our sample as a by-product of the estimation. We propose the construction of a synthetic indicator of global credit stance that can be interpreted as a measure of the evolution of the credit cycle in the advanced economies. Figure 1 plots the evolution of the average of the quarterly growth rate of real bank credit to the private sector (BCPS) for the countries considered in the study (left axis) and, anticipating the results shown below, the proposed synthetic indicator of global credit stance (right axis).<sup>3</sup> Looking at the raw data one can realize that there is a cyclical pattern in bank lending, however it is difficult to determine exactly what are the turning points since it sometimes shows a volatile behavior and periods of synchronized credit crisis among these countries. Our indicator includes information of the probability of being in a credit crisis for all the countries in our sample, and signals five episodes of global restrictions in bank lending over the last forty years: 1974-76, 1979-84, 1989-94, 2001-02, and from 2008 until the end of the period.

The rest of the paper is organized as follows. Section 2 presents a review of the literature, both from an empirical and from a theoretical perspective. Section 3 describes the data and the methodology used in the empirical exercise. Section 4 presents the estimation results of the proposed models for real credit growth and an analysis of these results at the country-level. Section 5 contains an application of the results obtained from the estimation of our preferred specification. Section 6 concludes.

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<sup>3</sup> The proposed indicator excludes data for Canada since the series for this country was only available until 2008:IV.

**Figure 1: Evolution of bank lending**



## 2 Literature Review

Several empirical studies have centered on the identification of periods of credit crisis that coincide with banking crisis episodes. Most of these works consist of case studies that are based on the evolution of variables related to developments in the financial sector and economic activity, giving rise to a set of banking crisis databases. Laeven et al. (2007) represents an example of this approach: They propose a database that covers the universe of systemic banking crises for the period 1970-2007 (extending the database provided by Caprio et al, 2005). Systemic banking crises are identified under some requirements that combine quantitative data with some subjective assessment of the situation. Bordo et al. (2001) provide a database of financial, currency and banking crises. They consider that an episode qualifies as a banking crisis when they observe financial distress resulting in the erosion of most or all aggregate banking system capital. This criterion is the same as the one followed by Carpio and Klingebiel (2003), who propose a survey of episodes of systemic and borderline financial crises for 93 countries. Reinhart and Rogoff (2008a, 2008b) provide a comprehensive database of banking crises for high and

middle-to-low income countries. Banking crises are identified through the analysis of events, marking a crisis episode whenever: (1) bank runs lead to the closure, merging, or takeover by the public sector of one or more financial institutions; and (2) the closure, merging, takeover, or large-scale government assistance of an important financial institution that marks the start of a string of similar outcomes for other financial institutions.

Another strand of the literature has centered on the analysis of the developments in the financial and banking sector prior and during credit crisis episodes. These studies have found a link between rapid credit growth and banking system fragility. For example, Kaminsky and Reinhart (1999) analyze episodes of banking and currency crises following the evolution of a set of macroeconomic indicators. They find that the growth rate of bank credit to the private sector accelerates as banking crises approach, remaining above the growth rate recorded in tranquil times. This finding is indicative of how bank credit can signal the upcoming of a crisis episode evolving as a leading indicator. Nevertheless, it is important to be aware of the fact that not always a period of rapid expansion in bank credit signals an overheating or a possible future banking crisis. For example, Cotarelli, Del’Ariccia and Vladkova-Hollar (2003) claim for a more positive assessment of credit booms following the literature that emphasizes the link between financial development and growth. They find that the acceleration in real bank credit in Central and Eastern European countries during 1998-2002 reflect overall financial deepening, the speed of privatization, crowding-in forces, and overall progress toward market institutions.

Regarding to the theoretical literature, some authors have proposed theoretical models as an attempt to explain the mechanisms that generate fluctuations in bank credit growth. Gorton and He (2005) support that credit cycles or periodic “credit crunches” are a result of changes in bank beliefs based on public information. Banks compete with each other relative to the credit standards that they apply and private information about prospective borrowers produced by a bank can affect rival lenders due to a “winner’s curse” effect. Some studies propose the existence of a link between the credit cycle and banking crises. Most of these models incorporate the “financial accelerator” as a common explanation of this linkage (Bernanke and Gertler, 1989 and 1990, or Kiyotaki and Moore, 1997). Inflated collateral values lead to a relaxation in the borrower’s credit constraint and contribute to excessively rapid credit growth. When business conditions worsen, borrowers’ net worth gets reduced, while increases agency costs for the banks.

As the worthiness of borrowers gets reduced fewer loans are made, generating a credit crunch that leads to a contraction in investment with negative effects on the real economy. There are also some proposals that link the credit cycle with the business cycle (which ultimately has consequences on the evolution of the banking sector). Rajan (1994) provides a theory of fluctuations in bank policies, arguing that rational bank managers with short horizons will set credit policies that influence and are influenced by other banks and demand side conditions. These fluctuations affect the evolution of credit, leading to a theory of low frequency business cycles driven by bank credit policies.<sup>4</sup>

### 3 Data and methodology

The main goal of this paper is to describe credit cycles and identify phases of particularly low (or negative) growth such as those that typically accompany financial or banking crises. We model the evolution of the quarterly growth rate of real bank credit to the private sector as a Markov-switching process using the methodology proposed by Hamilton (1989), considering an unbalanced panel of twelve advanced countries (those in the OECD G10 group plus Spain), over the period 1960:I-2010:I.

In this section we first present a brief description of the data used in the empirical exercise. Then, we present the basic Markov-switching autoregressive model for the standardized series of real credit growth, with which we intend to capture the evolution of the cyclical component of the dynamics of credit. We also present the specification of an enlarged version of the basic model, in which the mean of the process is also explained by the evolution of lagged GDP growth. This specification implies a new definition of the credit cycle, as the basis of which we extract the effect of the business cycle on swings in bank lending.

#### 3.1 The Data

We use quarterly data for a sample that includes those countries belonging to the OECD G10 countries plus Spain (G10 countries in the OECD grouping are Belgium, Canada, France, Ger-

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<sup>4</sup> Gorton and Winton (2003) provide a detailed and extended review of the literature about the effect of bank funding on lending and the consequences on the business cycle.

many, Italy, Japan, Netherlands, Sweden, Switzerland, United Kingdom and United States), for the period 1960:I-2010:I from the International Financial Statistics (IFS) of the International Monetary Fund (IMF). Our variable of interest is the quarterly growth rate of real bank credit to the private sector, constructed using data on net credit extended by the banking sector to non-financial corporations, households, and non-profit institutions deflated by the GDP deflator. Real output growth is also used in some specifications of the model and it is defined as the quarterly growth rate of real GDP, obtained from the quarterly country series of the OECD Economic Outlook.

**Table 1: Descriptive statistics: quarterly growth rate of real credit**  
(quarterly percentage rates)

	# Obs.	Sample period	Mean	S.D.	Max	Min
Belgium	200	1960:II - 2010:I	1.37	1.96	-2.77	6.51
Canada	195	1960:II - 2008:IV	1.45	1.98	-7.99	7.81
France	200	1960:II - 2010:I	1.34	1.82	-5.04	7.79
Germany	200	1960:II - 2010:I	1.07	0.92	-1.11	3.06
Italy	160	1970:II - 2010:I	0.91	1.34	-3.75	3.42
Japan	199	1960:II - 2009:IV	1.26	1.77	-4.99	7.62
Netherlands	200	1960:II - 2010:I	1.98	1.44	-1.30	6.50
Spain	152	1972:II - 2010:I	1.62	1.91	-3.03	7.28
Sweden	200	1960:II - 2010:I	0.92	2.45	-7.81	7.96
Switzerland	184	1964:II - 2010:I	0.90	1.22	-3.68	4.33
UK	200	1960:II - 2010:I	1.08	2.06	-5.96	5.92
US	200	1960:II - 2009:IV	0.86	1.43	-4.47	3.96

S.D.: Standard Deviation. # Number of observations.

Table 1 reports some descriptive statistics for real credit growth. There exists heterogeneity in the mean growth rates, ranging from values close to 0.90% for countries like Italy, Sweden or Switzerland, to values close to 2.00% as for Netherlands. There is also some cross-country heterogeneity related to the standard deviation of these series. There are countries with levels of dispersion higher than 2.00%, like the United Kingdom or Sweden, while other countries show a more stable pattern with standard deviations below 1.50%, like Germany or Switzerland. Some of the countries have experienced episodes of rapid expansion of real credit in just one quarter with rates of growth larger than 7%, like France, Japan, Spain or Sweden. Countries like Canada

and also Sweden register the record levels at the other extreme, with episodes of falls in real credit growth, with values close to  $-8.00\%$ .

## 3.2 Methodology

### 3.2.1 The basic Markov-switching autoregressive model

We assume that the basic autoregressive Markov-switching model (MS-AR) that describes the evolution of real bank credit to the private sector (real credit growth henceforth),  $\Delta c_{it}$ , at the country level can be specified as:

$$\Delta c_{it} = \omega_i(s_{it}) + \phi(\Delta c_{it-1} - \omega_i(s_{it-1})) + \sigma_i \epsilon_{it}, \quad (1)$$

$$\epsilon_{it} \sim iidN(0, 1),$$

where  $\phi$  is an autoregressive coefficient,  $\mu(\cdot)$  is a state-contingent mean,  $\sigma_i^2$  is the variance of the residuals, and  $s_{it}$  is the latent variable describing the state of the economy in country  $i = 1, \dots, N$  at period  $t = 1, \dots, T$ . This variable is assumed to follow a Markov chain  $\{s_{it}\}_{t=1}^T$  with  $S$  latent states,  $s_{it} \in 1, \dots, S$ , and transition probabilities,  $p_{kj}$ , defined as:

$$p_{kj} \equiv P(s_{it} = j | s_{it-1} = k),$$

$$\sum_{j=1}^S p_{kj} = 1 \quad \forall k \in \{1, \dots, S\},$$

for  $j = 1, \dots, S$ . In the analysis below, we will explore specifications of this basic model in which the latent state variable displays two ( $S = 2$ ) and three states ( $S = 3$ ).

We adopt a multi-country estimation approach following the strategy proposed by Ceron and Suarez (2006). The reason for this strategy is that there might be reliability problems with the estimates that are obtained using data for a single country, especially when the phases of the cycle that one is considering are long and the number of switches between states within the time series considered may be too small. However, the existence of unobserved heterogeneity between the economies and banking sectors of these countries may generate an identification problem, since the evolution of the latent state variable may capture permanent differences in real credit growth more than movements related to changes in regime. The proposed methodology addresses this identification problem by modeling the dynamics of our variable of interest as a

combination of a *country-specific component*, which is intended to capture unobservable cross-country heterogeneity, and a *cyclical component*, which could be modeled as a Markov-switching process with parameters common to all the countries.

In particular, we assume that the state contingent mean of the process is described as follows:

$$\omega_i(s_{it}) = \alpha_i + \mu(s_{it}) \cdot \sigma_i, \quad (2)$$

where  $\alpha_i$  and  $\sigma_i^2$  are identified as the unconditional mean and variance of real credit growth (which are *country-specific* and intended to capture unobserved heterogeneity) by assuming that the expectation of the *cyclical component* equals zero, that is:

$$E[\mu(s_{it})] = 0, \forall i. \quad (3)$$

Provided that the model presented in (1) coincides with the true data generating process for real credit growth, and assuming that (2) and (3) hold, permanent unobserved heterogeneity may be controlled by using the standardized transformation,  $\Delta d_{it}$ , of real credit growth,  $\Delta c_{it}$ , in the estimation of the Markov process for the cyclical part:

$$\Delta d_{it} = \frac{\Delta c_{it} - \alpha_i}{\sigma_i}. \quad (4)$$

We could also rewrite the specification of the basic model as follows:

$$\Delta d_{it} = \mu(s_{it}) + \phi(\Delta d_{it-1} - \mu(s_{it-1})) + \sigma \epsilon_{it}, \quad (5)$$

$$\epsilon_{it} \sim iidN(0, 1),$$

where the parameters of the MS process are assumed to be the same for all the standardized series, so that the transition probabilities are the same for all countries ( $p_{ij} = p_j$ ). It should be remarked that each country's latent state variable is treated as an independent realization of the same Markov-switching process, so that we are able to study the evolution of the probabilities of being in a given state over time for each of the countries.

Under these assumptions, the parameters of the model are estimated by adapting the estimation method proposed by Hamilton (1989) by considering as our objective function the sum of the likelihoods of the countries in our sample. The sample counterpart of the unconditional country-specific moments is used in order to obtain the standardized series. Here we proceed as



if the number of observations was large enough in order to avoid bias problems related to the presence of serial correlation in the data.

The period that we consider is large enough to contain some events related to structural changes in the historical evolution of real credit. Non-linear models tend to capture these movements as corner solutions in the estimation of the process. In a country-by-country approach, these changes may obscure the identification of periods related to credit crises. We conjecture that, by imposing the same Markov-switching structure on the cyclical component of all of the countries, the latent state variable is less likely to capture structural changes, given that these shifts tend to be less recursive than the phases related to real credit growth (Table A1 included in the Appendix contains descriptive statistics of real credit growth for several decades; they do not show remarkable changes in the mean growth rates of real credit growth for the different subperiods).

### 3.2.2 The enlarged version of the MS-AR model

In addition to our basic model, we also consider a specification in which (one-period lagged) real GDP growth affects the conditional mean of the credit growth's process:

$$\Delta d_{it} = \mu(s_{it}, \Delta gdp_{it-1}) + \phi(\Delta d_{it-1} - \mu(s_{it-1}, \Delta gdp_{it-2})) + \epsilon_{it}, \quad (6)$$

where

$$\mu(s_{it}, \Delta gdp_{it-1}) = \mu(s_{it}) + \beta(s_{it})\Delta gdp_{it-1}$$

and the specification of  $\epsilon_{it}$  remains unchanged. In fact, this specification implies an alternative definition of the credit cycle, in which cyclical shifts in the evolution of real credit growth captured by the non-linear MS-AR structure are those not linearly “explained” by shifts in the business cycle as captured by lagged GDP growth.

## 4 Estimation results

In this section, we report the results obtained from the estimation of the different specifications of the Markov-switching model presented in Section 2.2 for the standardized series of real credit growth,  $\Delta d_{it}$ . First, we explain the criterium used to select our preferred specification of the

model and comment on the parameter estimates obtained. Then, we explore the implications of the results for the country-level cyclicity analyzing the evolution of real credit growth through the probabilities of being in each of the possible states (obtained as a by-product of the estimation), and the implied conditional moments for the original country series. Finally, we briefly analyze the relationship of the bank credit cycle and the business cycle for the case of US as an illustration.

## 4.1 Estimation results

Table 2 presents a classification of the different models that are considered in this study. First, we focus on those specifications based on the basic MS-AR model specified in (5), which includes data on real credit growth exclusively. Models 1 and 3 refer to the two and three states MS-AR models respectively. Model 2 represents the basic model in which we impose the value of the mean growth rate of the second state. Then we present the results obtained from the enlarged version of the model specified in (6) with two and three latent states. This makes Models 4 and 5, respectively.

**Table 2: Overview table**

	Basic MS-AR		Enlarged MS-AR
	Unrestricted	Restricted	
Two states	Model 1	Model 2	Model 4
Three states	Model 3	-	Model 5

Table 3 summarizes our estimation results. These models are estimated including data for all the countries in the sample after standardization using the sample counterparts of the unconditional means and variances. The units of measure of the presented estimates are standard deviations of the original country variable, both for the state-contingent means as well as for the standard deviation of the process for the innovations.

Model 1 corresponds to the basic two-state ( $S = 2$ ) MS-AR model described in (5). The estimation uncovers two states that describe the evolution of real credit growth, which differ in their value for the mean growth rate. The high (low) growth state is described by a mean growth rate,  $\mu(1)$  ( $\mu(2)$ ), equivalent to 58.6% ( $-72.1\%$ ) of one standard deviation of the original series.

The autocorrelation parameter  $\phi$ , which significantly differs from zero, reflects the effect one period ahead of the deviation of the variable  $\Delta d_{it}$  with respect to the state contingent mean. A unit increase in this deviation has a positive effect on the following quarter, close to 30% of one standard deviation of the original series. The high (low) growth state has an expected duration of 19.2 (16.0) quarters and happens with an unconditional probability of 54.6% (45.4%).

A first view on the estimates obtained from Model 1, especially the expected durations of the states that turn out to be very similar and are above 4 years in both cases, points out that the cycle that it captures is more related to alternating phases of high and low credit growth rather than to periods of normality alternated with periods of abnormal or severe credit crunches, which is the main target of this paper. In order to improve the identification of credit crisis episodes, we conduct an empirical investigation through the estimation of Model 2 in which we restrict the parameter of the low growth mean  $\mu(2)$  to be equal to  $-1$  standard deviation. The point estimate for the high growth mean  $\mu(1)$  is now 46.7%, lower than the one obtained in the previous specification. This is an expected result since now the definition of the second state is stricter compared to the previous model, so that the first state includes periods of intermediate growth and credit expansions, while phases of credit crisis emerge as the second state. The expected duration of the low growth state is now shorter, around three years, while the high/intermediate growth state is now more persistent, being close to 5.5 years. The unconditional probabilities show the same pattern since the unconditional probability of being in a low growth state is smaller (35.1%), while episodes of high/intermediate growth happen more usually (64.9%). Model 2 represents a shortcut in the identification of periods of severe credit crunch that may be useful in those cases in which the econometrician is not interested in the evolution of the latent state variable away from the crisis phases. The problems of the restricted version of the model are that there is an important loss in the likelihood obtained from the estimation and it is not capable to disentangle phases of expansion from phases of intermediate credit growth. These disadvantages can be avoided through the specification of the model with 3 states.

Model 3 corresponds to the MS-AR model with three states ( $S = 3$ ) as it is specified in (5). The description of this model is the same as the one presented in (2) where, as a matter of convention, we expect  $s_{it} = 1$  to identify a “credit expansion” state,  $s_{it} = 2$  an “intermediate

**Table 3: Estimation results**  
(standard errors in parenthesis)

	Model 1	Model 2	Model 3	Model 4	Model 5
$\mu(1)$	0.586 (0.042)	0.467 (0.037)	0.808 (0.055)	0.586 (0.041)	0.803 (0.055)
$\mu(2)$	-0.721 (0.048)	-1.000 <sup>1</sup>	-0.185 (0.063)	-0.722 (0.047)	-0.201 (0.063)
$\mu(3)$	-	-	-1.212 (0.075)	-	-1.239 (0.077)
$\phi$	0.304 (0.025)	0.350 (0.026)	0.206 (0.034)	0.298 (0.026)	0.198 (0.035)
$\sigma^2$	0.529 (0.019)	0.527 (0.020)	0.456 (0.018)	0.281 (0.019)	0.452 (0.019)
p <sub>11</sub>	0.948 (0.009)	0.955 (0.008)	0.923 (0.013)	0.947 (0.009)	0.923 (0.014)
p <sub>22</sub>	0.937 (0.010)	0.916 (0.013)	0.924 (0.016)	0.938 (0.010)	0.922 (0.016)
p <sub>33</sub>	-	-	0.864 (0.011)	-	0.860 (0.012)
p <sub>12</sub>	-	-	0.045 (0.015)	-	0.047 (0.015)
p <sub>21</sub>	-	-	0.047 (0.011)	-	0.049 (0.012)
p <sub>32</sub>	-	-	0.095 (0.027)	-	0.100 (0.028)
$\Delta gdp_{-1}$	-	-	-	0.029 (0.017)	0.032 (0.016)
Expected Duration					
S1	19.2	22.1	13.0	19.0	13.0
S2	16.0	11.9	13.2	16.0	12.8
S3	-	-	7.4	-	7.1
Unconditional Probabilities					
S1	54.6	64.9	37.1	54.2	37.6
S2	45.4	35.1	44.8	45.8	44.9
S3	-	-	18.1	-	17.6
AIC	1347.8	1371.7	1293.3	1348.7	1284.0
BIC	1382.2	1400.3	1356.4	1388.8	1352.7
Log-likelihood	-667.9	-680.8	-635.7	-667.3	-630.0

<sup>1</sup> Imposed value in the estimation. Note:  $\mu(\cdot)$  is a state-contingent mean;  $\phi$  is an autoregressive coefficient;  $\sigma^2$  is the variance of the residuals;  $p_{kj}$  is the probability of shifting from state  $k$  to state  $j$ ;  $\Delta gdp_{-1}$  corresponds to the standardized quarterly growth rate of real GDP. AIC: Akaike's information criterion. BIC: Bayesian Information Criterion or Schwarz Criterion.

growth” state, and  $s_{it} = 3$  a “credit crisis” state. Credit expansions display a mean growth rate,  $\mu(1)$ , equal to 80.8% of one standard deviation of the original series while credit crisis phases have a mean growth rate equal to  $-121.2\%$ . Phases of intermediate growth are identified by the middle state, that emerges with a mean growth rate of  $-18.5\%$  of one standard deviation of the original series. Credit crises emerge as the less persistent and frequent state with an expected duration of 7.4 and an unconditional probability of being in this state of 18.1%. The expected duration of intermediate growth and credit expansion phases is similar (close to 2 years and a quarter), but intermediate growth phases are more frequent with an unconditional probability of 44.8% compared to 37.1% of credit expansion episodes. The point estimates of the transition probability matrix from Model 3 are:

$$\begin{bmatrix} p_{11} & p_{21} & p_{31} \\ p_{12} & p_{22} & p_{32} \\ p_{13} & p_{23} & p_{33} \end{bmatrix} = \begin{bmatrix} 0.923 & 0.047 & 0.041 \\ 0.045 & 0.924 & 0.095 \\ 0.032 & 0.028 & 0.864 \end{bmatrix}.$$

These estimates show that, once being in a credit crisis and given that the economy does not remain in the same state in the next period, the most likely event is to observe a shift into an intermediate growth episode, 9.5%, rather than into a credit expansion, 4.1%, pointing out the fact that rapid recoveries are not usual in the credit cycle. The same event happens when the banking sector is in a credit expansion, that is, given that it does not remain in a credit expansion phase the banking sector of these economies tend to go into an intermediate growth state (4.5%) rather than into a credit crisis (3.2%).

Model 3 achieves a richer and closer to intuition description of the “credit cycle” since it is able to separately identify periods of high growth, intermediate growth and credit crunch. This version is our preferred univariate specification within the models that just include real credit growth, hence we will use the outcomes obtained from this estimation in order to perform a deeper analysis. Relative to the selection of the number of states, in the context of Markov switching models, the usual tests (Likelihood Ratio, Wald, and Lagrange multiplier) do not have the standard asymptotic distribution because of the presence of nuisance parameters under the null hypothesis. Nevertheless, we should remark that there is an important gain in the likelihood obtained from this specification with respect to the model in which we allow for just two states. The information criteria of Akaike (AIC) and Schwarz (BIC) suggest that there

is a large enough increase in the goodness of fit obtained from the estimation of the three-state Markov-switching model compared to the restricted version.

The last two columns correspond to the augmented models that include real output growth as it is specified in (6). These models (Models 4 and 5) are estimated using the standardized series of real GDP growth, thus the units of measure of the estimates should be interpreted as deviations of the original country variable as in the previous cases. It is important to notice that when we include lagged GDP growth as an explanatory variable of the mean growth rate of real credit the latent definition of the “credit cycle” as captured by Markov-switching structure of the model changes. The latent state variable now captures shifts in the evolution of real credit growth after having discounted or filtered out the linear effect of the business cycle as captured by  $\Delta gdp_{it-1}$ . The specification in (6) allows the coefficient for  $\Delta gdp_{it-1}$  to vary across states, nevertheless the non-reported estimation results confirm that the coefficient for  $\Delta gdp_{it-1}$  does not significantly change with the latent state variable in neither Model 4 nor Model 5.

Model 4 stands for the enlarged version of Model 1, that is, the MS-AR model with two states ( $S = 2$ ) including lagged GDP growth as it is specified in (6). The estimated values for the state-contingent means of the process, as well as the estimated transition probabilities are similar to the ones obtained in the specification of the model without  $\Delta gdp_{it-1}$ . Lagged economic growth has a statistically non significant and quantitatively small positive effect on the mean of real credit growth. The inclusion of this variable in the model with two states seems to have little effect on the estimated non-linear structure for real credit growth.

Model 5 corresponds to the three-state version of the model including lagged GDP growth as an explanatory variable for the mean of the process. The inclusion of  $\Delta gdp_{it-1}$  has again a small effect on the estimates obtained. The difference between the estimated values for  $\mu(\cdot)$  between Model 3 and Model 5 is relatively small. We should be aware of the fact that in Model 5 the mean growth rate of real credit growth is also determined by lagged GDP growth, but  $\Delta gdp_{it-1}$  has zero mean (the model is estimated using the standardized series) so comparisons are still meaningful. We also tried other specifications including different combinations of the lags of  $\Delta gdp_i$ , where the coefficients for these extra variables were not significative.

Since the inclusion of lagged output growth does not improve the identification of credit crisis phases, we will consider the analysis of the results obtained from the estimation of Model 3 henceforth, in which the credit cycle is fully determined by the swings in real credit growth.

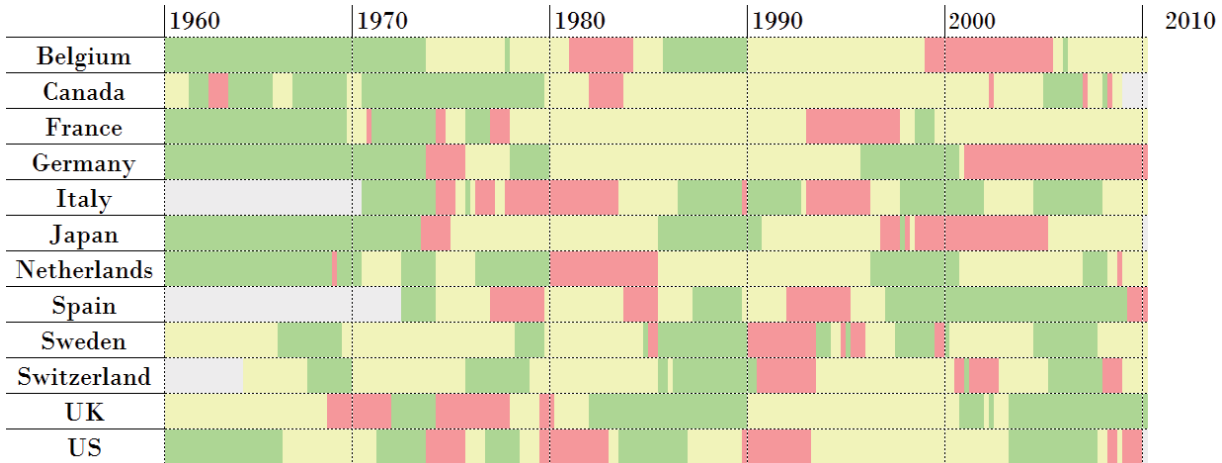
## 4.2 Analysis of the results

The estimation of Markov-switching models gives us the opportunity to look at the probabilities of being in each of the states over time and date the different phases of the credit cycle. The dating is based on the selection of the more likely state through a comparison of the “smoothed probabilities” of being in each of them, which are obtained following the procedure described by Hamilton (1989). We consider that the economy is in state  $s_{it} = j$ , ( $j = 1, 2, 3$ ), whenever:

$$P(s_{i\tau} = j|\Omega_{iT}) > P(s_{i\tau} = k|\Omega_{iT}), \forall k \neq j,$$

where  $T$  refers to the full sample period,  $\tau < T$  and  $\Omega_T$  contains the information until the last period. The smoothed probabilities, also called two-sided probabilities, use the evolution of real credit growth from the full sample period to estimate the probability of being in each state for a given quarter, and hence they are more accurate in the dating than the filtered probabilities that use only real time information.

**Figure 2: Heat Map: evolution of the credit cycle \***



\* Estimates are obtained from Model 3. Red indicates a credit crisis phase, yellow indicates an intermediate growth phase, and green indicates a credit expansion phase.

Figure 2 presents a graphical representation of the results obtained from the estimation of Model 3. The representation of the results through a heat map is useful, among others, in the



sense that it allows to see the different kinds of transition between states that these countries have experienced. For example, during the 1970s a half of the sample experienced sudden stops in the credit cycle, going from credit expansion to credit crisis phases (France, Germany, Italy, Japan, UK and US). This phenomenon tended to be less usual in the next decades, in which the landing after a credit boom was more gradual, entering into a period of intermediate growth well before the credit crisis began (Germany 2001, Spain 1990, US 1987 and 2007). On the other hand, credit crises in almost all cases ended with an intermediate growth phase, which is consistent with the aforementioned idea that rapid recoveries are not usual in the credit cycle.

Table 4 provides the dating of credit crises episodes for each of the countries in our sample, while Figure 3 shows the evolution of the smoothed probabilities of being in a credit crisis and in a credit expansion phase for each country as determined by Model 3 together with the evolution of the standardized series of real credit growth. Our model identifies various credit crisis phases experienced in the past, which coincide with some of the periods of financial or banking crises that the literature has previously recognized. For example, the credit crises identified for Spain (1977), Sweden (1991) or Japan (middle 1990s) belong to the Big Five financial crises studied by Reinhart and Rogoff (2008). Our model also identifies some of the episodes of systemic and non-systemic banking crisis proposed by Honohan and Laeven (2005), and Laeven et al. (2007).

Table 4: Dating of credit crisis peaks and troughs

COUNTRY	Dating
Belgium	1981:I-1984:I, 1999:I-2005:II.
Canada	1962:IV-1963:III, 1982:I-1983:III, 2007:I-2008:II.
France	1970:IV, 1974:II-1974:III, 1977:I-1977:IV, <i>1993:I-1997:III</i> .
Germany	<i>1973:IV-1975:III</i> , 2001:I -
Italy	1974:II-1975:I, 1976:II-1977:I, 1977:IV-1983:II, 1989:IV-1990:I <i>1993:I-1996:I</i> .
Japan	1973:III-1974:IV, <i>1996:IV-1997:III</i> *, 1998:I, 1998:III-2005:I
Netherlands	1969:I, 1980:I-1985:II, 2008:IV.
Spain	<i>1977:I-1979:III</i> *, 1983:IV-1985:II, 1992:I-1995:I, 2009:II -
Sweden	1985:I-1985:II, <i>1990:I-1993:II</i> *, 1994:IV, 1995:II-1995:IV, 1999:III-1999:IV.
Switzerland	1990:III-1993:II, 2000:III-2000:IV, 2001:II-2002:III, 2008:I-2008:IV.
UK	1968:IV-1971:IV, <i>1974:II-1977:IV</i> , 1979:III-1980:I.
US	1973:Iv-1975:III, 1979:III-1982:IV, <i>1989:IV-1993:I</i> , 2008:II-2008:III, 2009:I -
<p>The dating of the credit crisis episodes is based on the smoothed probabilities obtained from Model 3.</p> <p>* denotes the “Big Five” financial crises (Reinhart and Rogoff, 2008a.)</p> <p><i>Italics type</i> denotes systemic banking crisis episodes (Laeven and Valencia, 2008, and Honohan, Patrick and Laeven, 2005).</p>	

The results identify six economies which have shifted into phases of credit crisis since 2008 (Canada, Germany, Netherlands, Spain, Switzerland and United States). It is remarkable that almost all of the countries considered in our study are identified as experiencing episodes of restrictions in bank lending during the financial crisis of 2007-2009, either in form of a credit crisis or a period of intermediate credit growth. This synchronization across countries seems one of the most notable consequences of the last financial crisis with respect to bank credit. In fact, some nations have experienced a change in the rate of growth of credit slightly different from what has been observed during credit crises, shifting from periods of credit boom into intermediate growth phases. Model 3 identifies eight of these economies as having experienced a credit expansion phase during 2006 and a rapid shift into periods either of a credit crisis or intermediate growth from the second quarter of 2008. These events could be linked to the view proposed by Schularick and Taylor (2009), who demonstrate that credit growth is a predictor of financial crises and suggest that such crises are “credit booms gone wrong”.

Analyzing the evolution of the smoothed probabilities obtained from the estimation of the model, one can observe how the dynamics of credit summarize the developments that usually take place around financial crisis episodes. For example, prior to the Nordic banking crisis, the bank lending sectors of some Nordic countries experienced an important credit boom. Figure 3 plots, among others, the smoothed probabilities of being in a credit crisis and in a credit expansion (right axis), together with the standardized quarterly growth rate of real credit (left axis), for Sweden as an illustration of these developments. The smoothed probability of being in an intermediate growth phase can be trivially inferred as a residual of the two depicted ones:

$$P(s_{i\tau} = 2|\Omega_{iT}) = 1 - P(s_{i\tau} = 1|\Omega_{iT}) - P(s_{i\tau} = 3|\Omega_{iT}), \tau < T.$$

A period of rapid expansion in bank lending to the private sector is identified by our model which started in 1985:III and ended five years later, in 1990:I, with a credit crunch that coincides with the Nordic banking crisis.

Our model identifies two large economies that have experienced a large recent phase of contraction (or very moderate growth) in bank credit: Germany and Japan. In the case of Germany, one can observe how after five years of credit expansion (1995-2000) the banking sector entered into a period of restrictions in bank lending that emanated into a credit crunch.<sup>5</sup> The smoothed probability of being in a credit crisis remains high for Germany basically until the end of the sample period, and hence does not indicate that the country exited from a credit crisis period. In many respects this development is reminiscent of the beginning of the banking crisis in Japan in the early 1990s (Westermann, 2003). This country experienced a lending boom in the late 1980s in parallel with the asset price bubble that burst in 1991. The effects of the bubble's collapse on bank lending are captured as an intermediate growth phase by our model, followed by a credit crisis that started in 1997 after increased loan losses (charge-offs and provisioning) that led to more bankruptcies in Japan (Nakaso, 2001). From 2005 onwards, our model captures how this economy has entered into a period of intermediate credit growth, with a modest improvement in bank lending. The magnitude of the problem clearly differs between Germany and Japan, but development of credit extended by their banking sectors are rather similar.

For various countries belonging to the euro area, our model captures asymmetric shocks in their bank lending. The slowdown of credit in Germany coincided with rapid expansions in Italy and Spain. These countries have experienced one of the largest booms in credit observed over the sample period and, while it has ended with a severe credit crunch in Spain starting in 2009:II, the landing in Italy has been relatively less painful entering into an intermediate growth phase from 2008:I onwards. Relative to the rest of euro area countries in our sample, i.e. France and Belgium, the results suggest that the effects of the financial crisis of 2007-2009 have been relatively small compared to countries like Spain or United States, since both of them remain in a period of intermediate credit growth.

Table 5 presents the recovered values for the conditional means and standard deviations implied by the model for each of the countries together with the number of credit crisis phases identified for each of the countries. The implied conditional moments can be easily recovered given the estimates of  $\alpha_i$  and  $\sigma_i$  presented in Table 1, together with the parameter estimates of

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<sup>5</sup> Nehls and Schmidt (2003) find evidence of a credit crunch starting in Germany in 2001.

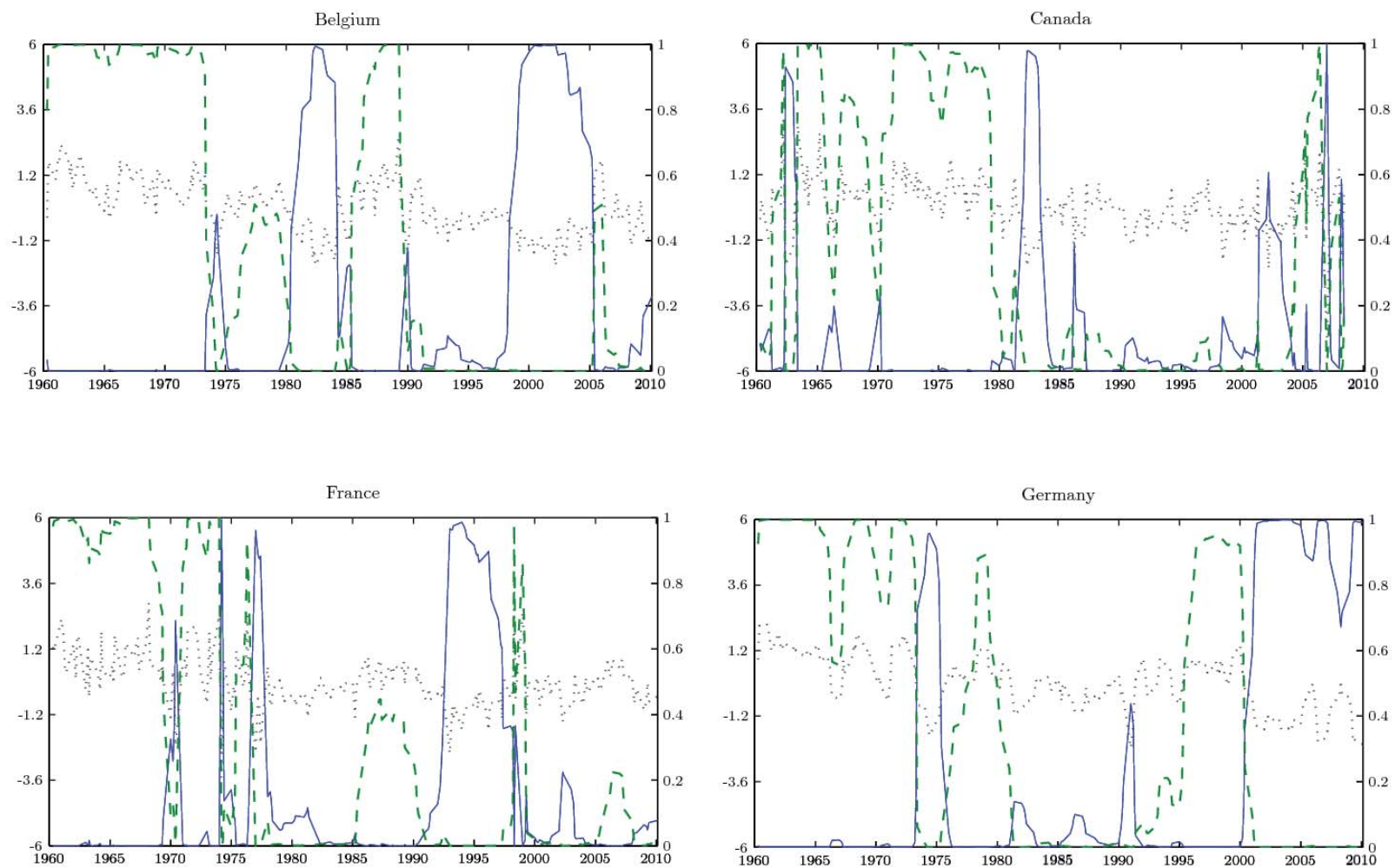


Figure 3: Probabilities of being in credit crisis & credit expansion (Model 3)

— Prob. of credit crisis (right axis)    - - - Prob. of credit expansion (right axis)    .. Data  $\Delta d_{it}$  (left axis)

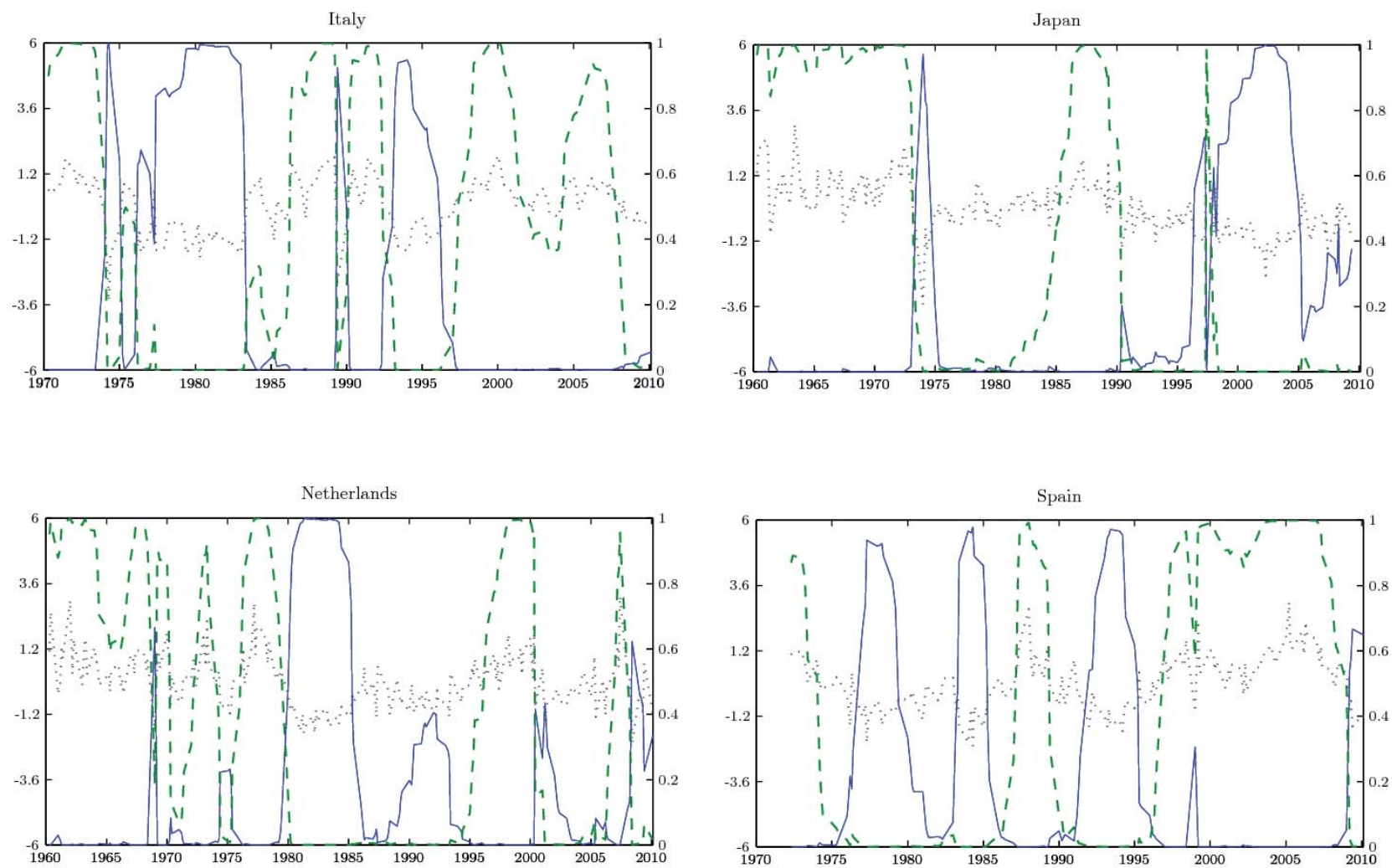


Figure 3: Probabilities of being in credit crisis & credit expansion (Model 3) - continuation

— Prob. of credit crisis (right axis)    - - - Prob. of credit expansion (right axis)    .. Data  $\Delta d_{it}$  (left axis)



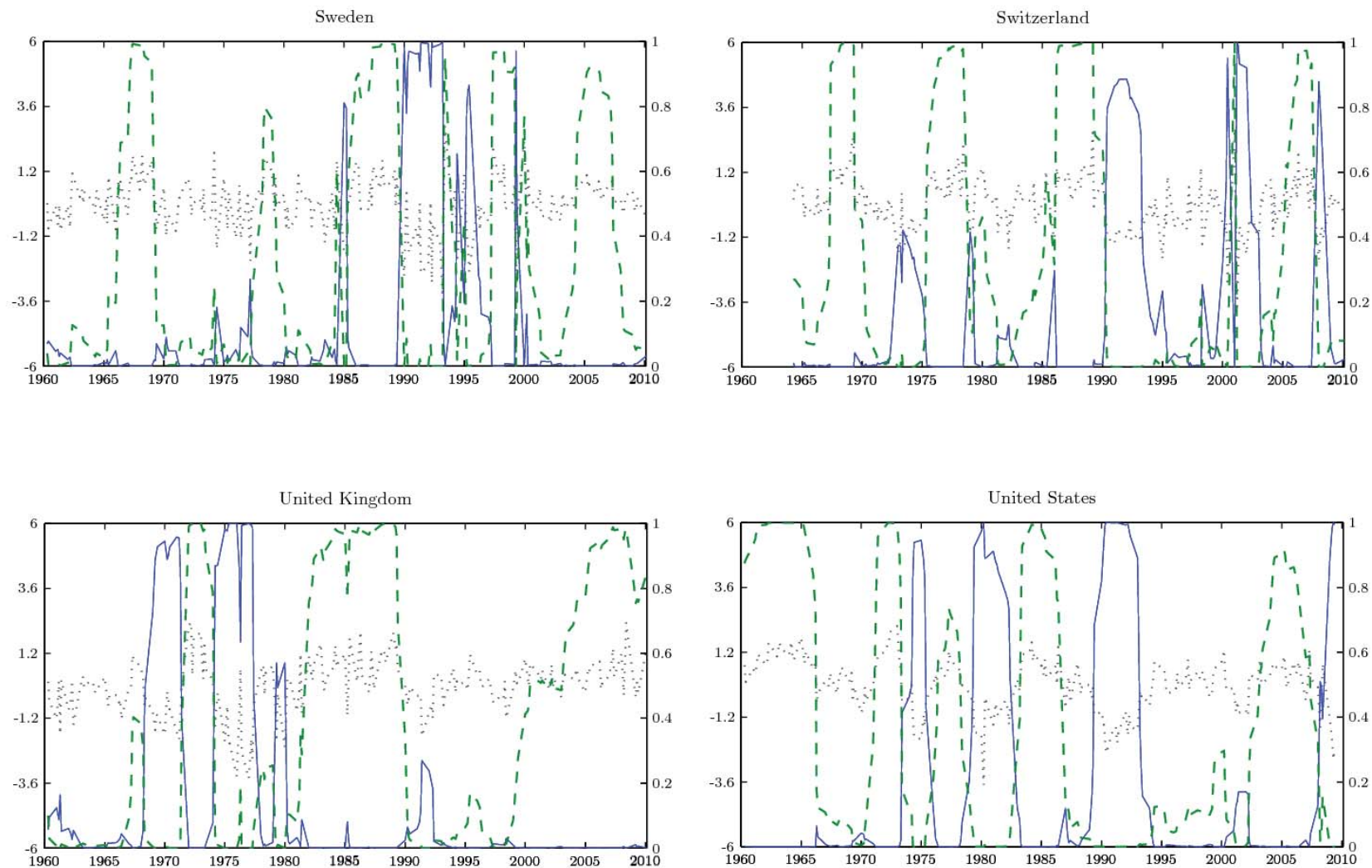


Figure 3: Probabilities of being in credit crisis & credit expansion (Model 3) - continuation

— Prob. of credit crisis (right axis)    - - - Prob. of credit expansion (right axis)    ... Data  $\Delta d_{it}$  (left axis)

Model 3 presented in Table 2. Credit expansion implies an expected mean growth rate of private sector credit over 3% for some countries (Canada, Netherlands and Spain), while for countries like Germany, Italy and Switzerland it implies values close to 2%. Expected mean growth rates in the intermediate growth state range from 0.46% (Sweden) to 1.72% (Netherlands). Relative to credit crises, we can observe that the expected mean growth rates of private sector credit are negative for almost all countries with Belgium, Sweden and United Kingdom at the lower tail of the distribution. Advanced economies have experienced an average of three complete phases of credit crisis over the sample period. However, the number of crises varies significantly across countries, with some experiencing only two crisis phases (Belgium and Germany) and others four or more (France and Italy).

**Table 5: Conditional moments**  
(quarterly percentage rates)

	$\omega(1)$	$\omega(2)$	$\omega(3)$	$\sigma$	# Crises
Belgium	2.95	1.00	-1.01	1.36	2
Canada	3.05	1.08	-0.96	1.38	4
France	2.81	1.01	-0.86	1.27	4
Germany	1.81	0.89	-0.06	0.64	2
Italy	2.00	0.66	-0.72	0.93	5
Japan	2.69	0.93	-0.90	1.23	4
Netherlands	3.14	1.72	0.24	1.00	3
Spain	3.17	1.27	-0.69	1.33	4
Sweden	2.89	0.46	-2.05	1.70	5
Switzerland	1.88	0.68	-0.57	0.85	4
UK	2.74	0.69	-1.43	1.44	3
US	2.02	0.60	-0.87	1.00	5
Average	2.60	0.92	-0.82	1.18	3.75
S.D.	0.52	0.34	0.58	0.30	1.05

Note: conditional means and variances recovered from the estimates of Model 3. Average: mean over the 12 countries. S.D.: standard deviation. # Crises: number of credit crisis phases identified within each country.

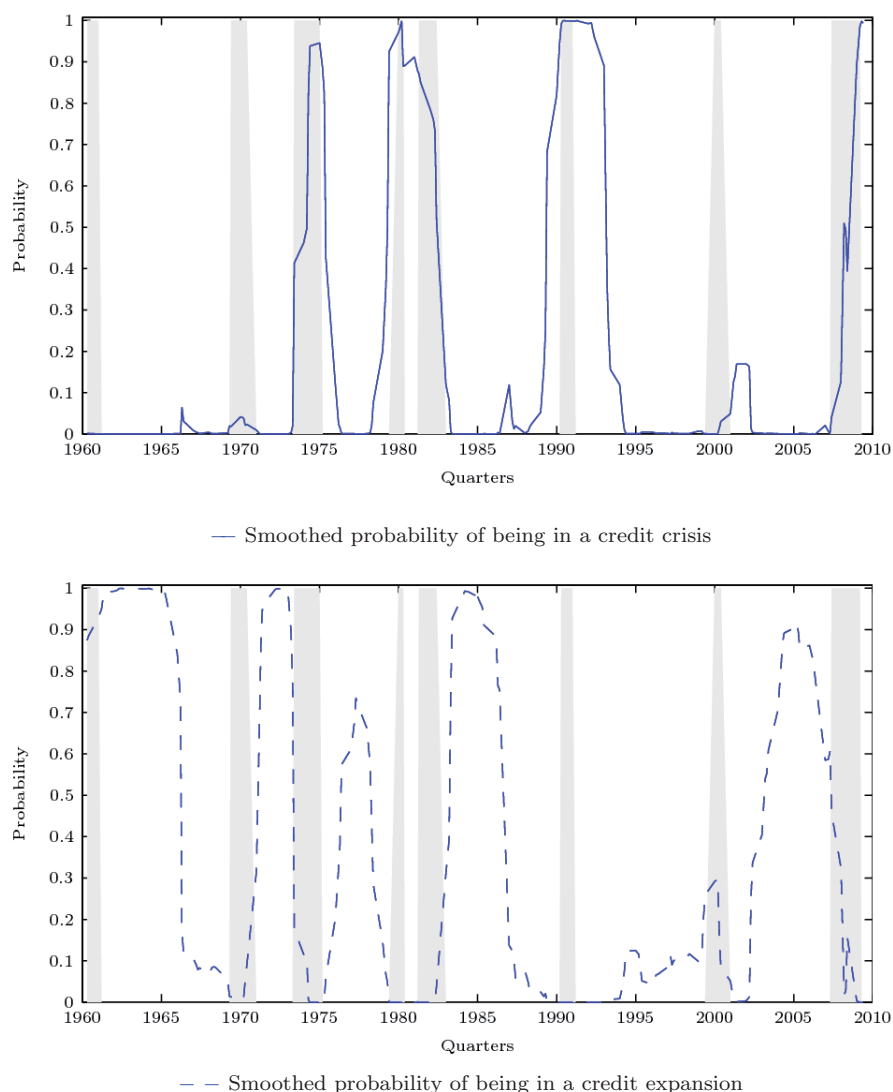
### 4.3 Relationship between bank credit and the business cycle

One can also analyze the different links that exist between the evolution of bank credit and the business cycle. As an example, Figure 4 plots the smoothed probabilities of being in a credit crisis state (top panel) and credit expansion state (bottom panel) for the case of United States together with the National Bureau of Economic Research (NBER) dating of the US recessions.

There is a close relationship between the evolution of the real economy and developments in the banking sector linked with real credit growth. Four of the recessions in the last 50 years



**Figure 4: Comparison: evolution of bank lending vs. NBER recessions**  
(shaded areas denote NBER recessions)



have been accompanied by episodes of a credit crunch, which correspond to the periods 1973-1975, 1979-1982, 1989-1993, and from 2008 to the end of the sample. Relative to the recessions experienced in early 1970s and in 2001 one can observe that, although the model does not assign the credit crisis state, there is an increase in the probability of being in that state, in fact the model identifies the slowdown in real credit as episodes of intermediate growth.

In principle, effects can flow from economic conditions to bank lending decisions and viceversa. The recessions of the 1980s and the 1990s started after the beginning of their respective credit crisis, and hence possibly the credit growth slowdown drove the shift in the real economy. If banks are an important source of funds for consumers and firms, an specific shock that affects bank lending may reduce borrowers' ability to invest or consume, leading to a slowdown in economic activity ("bank lending channel"). On the other hand, we find that, for the recessions experienced in the early 1970s and the current financial crisis, real credit growth displays a

lagged behavior with one and two quarters of difference, respectively, compared to the beginning of the recession. In this context, the worsening in business conditions possibly increases the risk of many potential borrowers reducing their creditworthiness and making banks more conservative (“credit risk channel”).

## 5 Constructing synthetic indicators of global credit stance

In this section we present an application of the results obtained from the estimation of the model. First, we present a synthetic indicator of the global credit stance that includes information on the evolution of bank lending in each of the advanced economies in our sample. Then, we study the degree of synchronization that exists between these economies and the relationship of our indicators of credit crisis with a variable that reflects the change in credit standards applied by the bank lending sector.

One of the advantages of working with a panel of countries is that we are able to analyze the credit cycle for different regions that include multiple countries simultaneously. We propose the construction of an indicator of the probability of being in a credit crisis for a multiple set of countries as an average of the smoothed probabilities of being in a credit crisis ( $P(s_{it} = 3|\Omega_{iT})$ ) obtained from the estimation of Model 3.

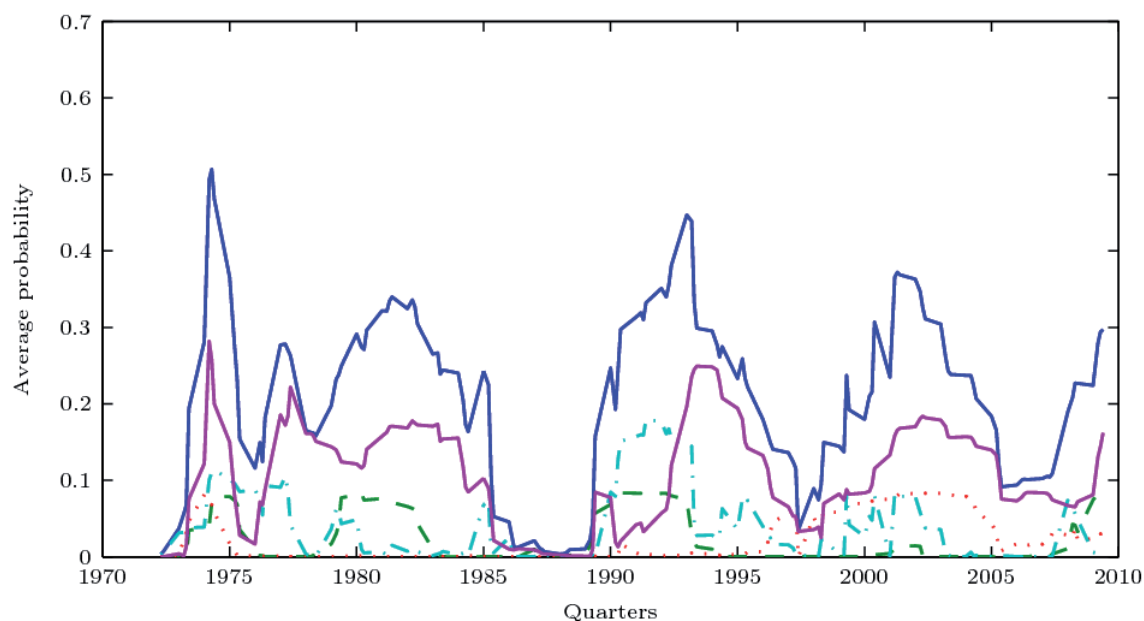
Figure 5 plots the proposed indicator, together with the contribution of the countries from different areas: United States, Japan, Europe I (countries belonging to the euro area) and Europe II (European countries that do not belong to the euro area).<sup>6</sup> This indicator could be interpreted as a measure of the evolution of the credit cycle at a global level for the advanced economies. We can observe a systematic cyclical pattern in the evolution of bank credit for these developed economies during the last forty years, with five episodes of global restrictions in real credit growth: 1974-75 (oil crisis), 1980-82 (second oil crisis), 1991-93 (Nordic crisis and savings and loans crisis in the United States), 2001-02 (end of the dot-com bubble) and from 2008 to the end of the sample (financial crisis).

The proposed indicator is not able to fully capture the degree of synchronization between the credit cycles of these countries. As we remarked in the previous section, maybe the most remarkable consequence of the current financial crisis over the evolution of lending in advanced economies is the synchronization in the slowdown in credit growth, with a joint shift of these economies from periods of expansion into periods of intermediate growth or credit crisis episodes.

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<sup>6</sup> The proposed indicator excludes data from Canada since data for this country was only available until 2008:IV.

Figure 5: Synthetic indicator of global credit stance



Contributions: - Synthetic indicator  
 - - United States - Europe I (euro) - - Europe II (non-euro) . . Japan

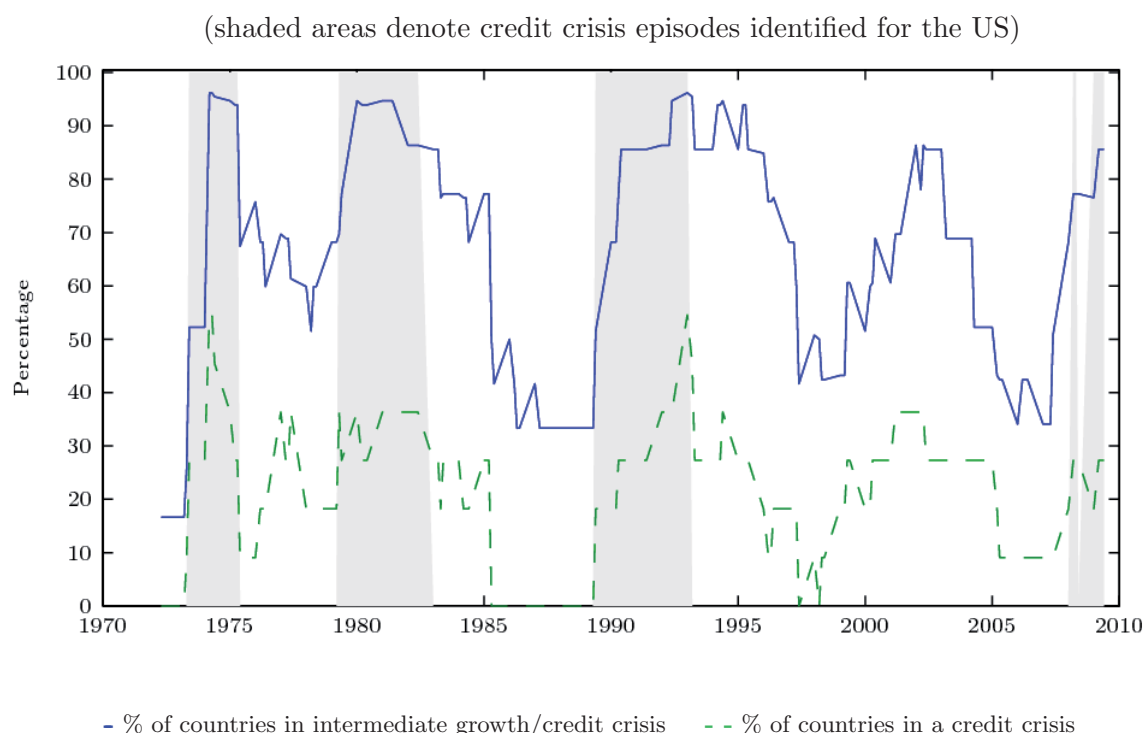
*Europe I (euro countries):* Belgium, France, Germany, Italy, Netherlands and Spain.

*Europe II (non-euro countries):* Sweden, Switzerland and UK.

Figure 6 plots the proportion of countries being in a credit crisis ( $s_{it} = 3$ ) and the proportion of countries being either in a credit crisis or in a period of intermediate credit growth ( $s_{it} = 2, 3$ ). The shadow areas correspond to those credit crisis episodes that the model identifies for the United States, which has been at the center of synchronous credit crises in almost all of the phases of global restrictions in bank lending. This country seems to lead the evolution of the credit cycle at the international level, experiencing credit crisis phases earlier and recovering the pace of credit growth when the rest of the economies have just entered in periods of bank lending restrictions.

It may be interesting to link the results to those obtained from bank lending surveys. The use of these surveys has become popular among analysts of bank credit developments. For example, Lown and Morgan (2006) find that credit standards strongly dominate loan rates in explaining variation in business loans. In Figure 7 we plot the evolution of the probability of being in a credit crisis for the United States (top panel) and the evolution of the synthetic indicator for the euro area (bottom panel) together with a measure coming from bank lending surveys that represents the change in credit standards required by commercial banks. For the case of United States, this variable is provided on a quarterly basis by the Federal Reserve (collected from the Federal Loan Officer Opinion Survey) as the net percentage of respondents reporting tightening

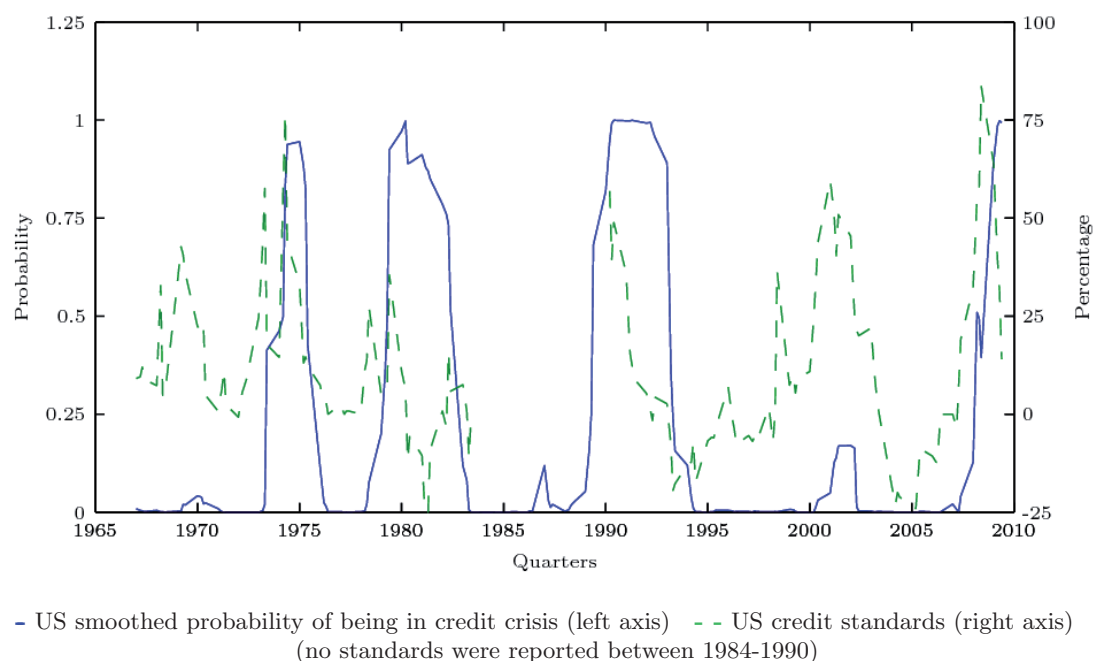
**Figure 6: synchronization of the cycle**



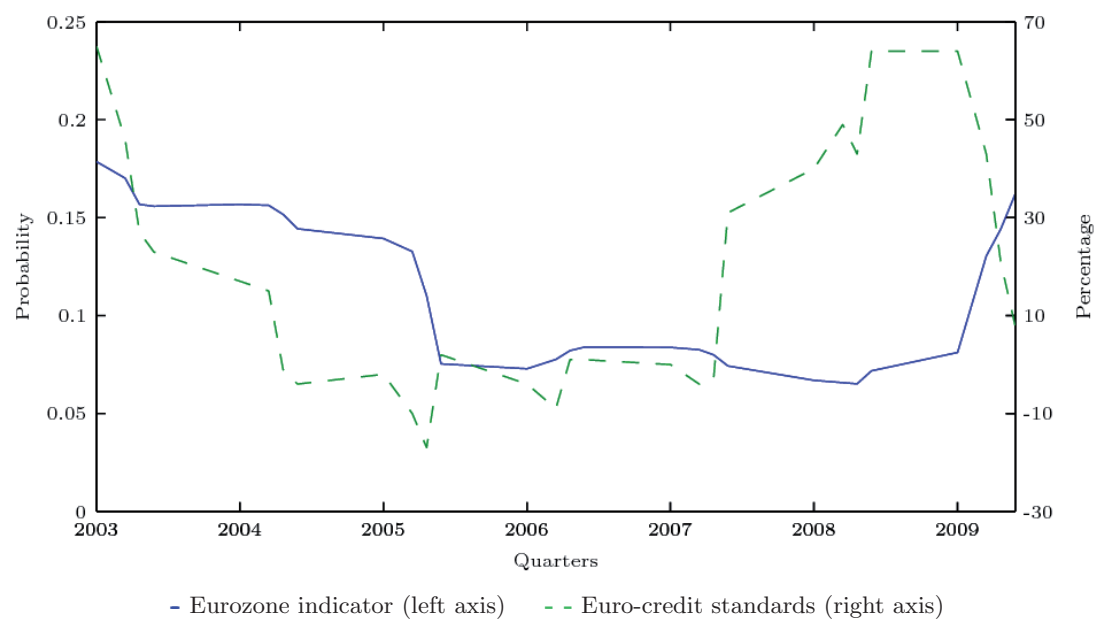
credit standards over the last three months. Importantly, the behavior of this variable leads the evolution of real credit over the full sample period: For example, in 2006 we find an increase in the percentage of banks reporting a tightening of credit standards while the slowdown in real credit growth started in 2007, one year later.

In the bottom panel of Figure 7, we plot the synthetic indicator for the euro area countries (constructed as an average of their smoothed probabilities of being in a credit crisis) together with the evolution of the variable for credit standards, which comes from the Euro Area Bank Lending Survey (provided by the European Central Bank on a quarterly basis). Although much less definitive due to the heterogeneity present among euro area countries, we observe the same qualitative pattern as in the case of United States: The change in this variable leads the evolution of real credit for the group of countries belonging to the euro area. For example, in the second quarter of 2007 euro-banks were already tightening their lending standards while the evolution of real credit growth did not start to moderate until the first quarter of 2008 (the moment at which the indicator reflects an increase in the probability of being in a credit crisis for the euro area).

Figure 7: Probability of being in a credit crisis vs. credit standards United States



### Euro area



Euro area countries in our sample: Belgium, France, Germany, Italy, Netherlands and Spain.

## 6 Conclusions

We have analyzed the credit cycle for a sample of twelve developed countries over the last fifty years. In our preferred specification, the evolution of the cyclical component of credit dynamics is characterized as a three-state Markov-switching model in the same fashion as Ceron and Suarez (2006). Under this proposal the estimation method proposed by Hamilton (1989) is adapted in order to take advantage of the joint estimation of the model, assuming that the evolution of the standardized series of real bank credit to the private sector of each country is an independent realization of the same Markov process.

Under this specification, the development of bank credit of a given country can be in either a “credit expansion”, an “intermediate growth”, or a “credit crisis” phase. Credit crisis phases have a mean growth rate of  $-121.2\%$  of one standard deviation of the original series and they are found to be the least persistent state, with an expected duration of 7.4 quarters and an unconditional probability of 18.1%. Credit expansion phases have a mean growth rate of 80.8% and they last around 13.0 quarters with an unconditional probability of 37.1%. Intermediate growth phases have a mean growth rate of  $-18.5\%$  of one standard deviation of the original series with an expected duration of 7.4 quarters and a frequency of 44.8%. On average, advanced economies have experienced three complete phases of credit crises over the sample period.

We find that six of the countries have experienced a credit crisis after the beginning financial crisis of 2007-2009 (Canada, Germany, Netherlands, Spain, Switzerland and US). By the end of the sample, three of these countries were still in a credit crisis episode (2010:I for Germany and Spain; and 2009:IV for United States). We also find that there exists a synchronization between the credit cycles of these economies, which have experienced five episodes of synchronous restrictions in bank lending during the last forty years: 1974-75 (oil crisis), 1980-82 (second oil crisis), 1991-93 (Nordic crisis and savings and loans crisis in the United States), 2001-02 (end of the dot-com bubble) and from 2008 to the end of the sample (financial crisis). Comparisons between the evolution of the smoothed probability of being in a credit crisis and the credit standards required by commercial banks suggest that the latter lead the credit cycle in the case of the United States (and also in the case of the Euro Area, although the result is much less definitive due to the heterogeneity present among euro area countries), which coincides with the results found previously in the literature (Lown and Morgan, 2006) that remark the explanatory power of this variable in the evolution of bank lending.

Relative to the dating obtained, our model identifies more credit crisis episodes than are typically identified with less formal techniques. Our episodes include some periods of financial

or banking crises that the literature has previously recognized. For example, we find credit crises for Spain (1977), Sweden (1991) or Japan (middle 1990s) which belong to the Big Five financial crises studied by Reinhart and Rogoff (2008). Our model also identifies some of the episodes of systemic and non-systemic banking crisis proposed by Honohan and Laeven (2005) and Laeven et al. (2007).

This paper has described the evolution of the credit cycle. Once we are able to identify the swings in credit the next step is to understand what are the forces that cause these swings, which is left for future research. Some ways for future research may be the inclusion of time-varying transition probabilities in order to test which variables lead the evolution of the credit cycle, and allow for interdependencies between the dynamics of credit for these economies in the estimation process as a way to describe better the synchronization found in our study.



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# Appendix

**Table A1: Descriptive Statistics by decade**  
(quarterly percentage rates)

	1960s	1970s	1980s	1990s	2000s	All
Belgium	3.17	2.06	1.20	0.47	0.03	1.37
Canada	2.24	2.54	0.83	0.75	0.84	1.45
France	2.90	1.27	1.16	0.50	0.95	1.34
Germany	2.08	1.25	0.77	1.21	0.10	1.07
Italy	0.00	0.74	0.66	0.88	1.37	0.91
Japan	2.78	1.44	1.86	0.59	-0.33	1.26
Netherlands	2.92	2.64	0.72	1.88	1.82	1.98
Spain	0.00	1.14	1.20	1.11	2.98	1.62
Sweden	1.42	0.90	1.27	-0.54	1.59	0.92
Switzerland	1.57	0.91	1.40	0.33	0.59	0.90
UK	0.37	-0.04	2.27	0.74	1.97	1.08
US	1.78	0.95	0.65	0.20	0.75	0.87
Average	1.77	1.32	1.17	0.68	1.06	1.23
S.D.	1.14	0.77	0.50	0.60	0.94	0.34

Average: mean over the 12 countries. S.D.: standard deviation.

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