Short-run dynamics in bank credit: Assessing nonlinearities in cyclicality

October 19, 2013

Abstract

This paper explores whether the procyclicality of private credit changes during the business cycle. To this end, we rely on the estimation of smooth transition regression models for a sample of 17 OECD countries over the 1986-2010 period. Our findings show that credit procyclicality is nonlinear, depending on economic conditions. More specifically, credit is highly procyclical in extreme—booms and busts—regimes in Canada, the UK and the US, while procyclicality is less pronounced in one or both extreme regimes in Australia, Belgium, France, Finland, the Netherlands, Norway, and Spain. Our results also emphasize the importance of financial factors in explaining the short-run behavior of private credit.

JEL Classification: C33, E32, E51, G21.

Keywords: Credit cycle, business cycle, nonlinearity, smooth transition regression models.

1 Introduction

The linkage between credit and the business cycle has been widely discussed in the literature, which generally emphasizes that the credit market is highly procyclical.[1] Indeed, a well established fact is that lending often increases significantly during business cycle expansions, and then falls considerably during subsequent downturns. The question of credit procyclicality has recently become even more important since there is now some consensus that the period leading up to the recent crisis was preceded by strong credit growth, combined with a speculative asset price bubble (Borio and Drehmann (2009)). When this bubble burst, it gave place to a deep banking crisis, accompanied by a severe economic recession.

Even though the specific causes explaining credit procyclicality—among supply-side, demand-side or regulatory-side factors—are still a subject of considerable debate,[2] the overall consideration of credit procyclicality is implicitly based on the hypothesis that both expansion and recession phases have the same effect (in absolute value) on the credit cycle. This symmetry implies that a change in the output gap of a given magnitude will therefore have the same impact regardless of whether it occurs during a recession or during an expansion.

In this paper, we investigate whether the effect of business cycle on credit cycle—i.e. credit procyclicality—is stable over time. Nonlinearities or asymmetries in this relationship could indicate that the strength of credit cycle determinants varies over the phases of the business cycle, a characteristic that would have important implications in terms of banking regulation.

[1] Regarding empirical contributions, see e.g., Borio et al. (2001), Goodhart et al. (2004), White (2006), Jiménez and Saurina (2006), Goodhart and Hofmann (2008), Bouvatier et al. (2012), and the references therein. For theoretical considerations, see Gorton and He (2008) and Aikman et al. (2011) among others.

[2] See Aikman et al. (2011) for a survey.

Indeed, the credit cycle is mainly driven by the business cycle, but the stability over time of this relationship can be questioned. Credit cyclicality could be more or less pronounced according to economic conditions leading to different short-run dynamics between boom and bust periods and/or between countries. Furthermore, the general conception that recession phases develop rapidly and are short-lived while expansion phases develop slowly and are more prolonged calls into question the linearity assumption of credit cyclicality.

Assessing this asymmetry allows us therefore to identify more accurately the main determinants of expansionary and contraction phases in bank credit. This point could be relevant for the banking regulator—or the macro-prudential regulator—to detect the emergence of boom periods and to identify which regulatory instrument is appropriate to curb bank lending. For example, a loan-to-value ratio regulation (Borio et al. (2001)) could be an appropriate regulatory instrument to curb bank lending if boom periods are more driven by property prices than by the business cycle. Similarly, government interventions to support the financial sector during recessions—as recapitalization, guarantees, asset purchases, and liquidity support—could be particularly appropriate if credit cyclicality is magnified during downturns.[3]

Remarkably, the empirical literature on bank credit is mainly based on linear estimations and focus on long-term determinants.[4] Only a few studies have investigated potential non-linearities in the bank credit dynamics. For instance, Gambacorta and Rossi (2010) show that the effect on credit, GDP and prices of monetary policy tightening is larger than the effect of monetary policy easing in the euro area. Relying on Markov-switching models,

[3]See Laeven and Valencia (2011) concerning government intervention packages and the effects during the recent financial crisis.

[4]See for example Calza et al. (2003), Hofmann (2004) or Calza et al. (2006).

Kakes (2000) finds that interest rate shocks have an asymmetric effect on credit, depending on the business cycle phase, for the US, Germany, Belgium and the UK, but not for the Netherlands. Markov-switching models have also been used to identify instabilities in short-run dynamics. Frömmel and Schmidt (2006) find evidence of unstable regimes for several European countries during which bank credit does not return to its long-run trend. In addition, stock market conditions seem important to explain credit fluctuations during these less stable regimes. With a similar methodology, Eller et al. (2010) examine Central, Eastern and Southeastern European (CESEE) countries and show that the short-run credit dynamics is characterized by a regime switching mainly driven by credit supply factors.

As a result, the empirical literature that studies credit procyclicality did not, to the best of our knowledge, investigate potential nonlinearities in the impact of the business cycle on the credit cycle. We aim at filling this gap by focusing on bank credit short-run fluctuations, and paying special attention to credit market asymmetries in relation to the business cycle in 17 OECD countries over the 1986-2010 period. To this end, we start by testing if the relationship between credit and GDP cycles is linear, i.e. whether credit is linearly procyclical. For those countries for which the linearity hypothesis is rejected, the asymmetry is captured through the estimation of smooth transition regression (STR) models. These models allow us to distinguish the effects of GDP on credit, depending on a transition variable. More specifically, in the STR specification, two extreme regimes—"booms" and "busts"—corresponding to two distinct credit equations, are endogenously determined. The transition from one regime to the other is smooth and governed by the transition variable. A large set of transition variables is considered in order to capture differences between countries. Indeed, depending on the country, nonlinearities in procyclicality could rather be related to conditions in credit market, stock market or property market rather than being associated with the business cycle phases.

The rest of the paper is organized as follows. Section 2 is devoted to the presentation of the retained methodology. Section 3 describes the data and provides some stylized facts concerning credit cycles and credit procyclicality. Estimation results are displayed in Section 4, and Section 5 concludes the article.

2 Methodology

As a first step, the procyclical character of credit can be analyzed relying on the simple following relationship:

$$\hat{l}_t = \phi_0 + \phi_l \hat{l}_{t-1} + \phi_y \hat{y}_{t-1} + \epsilon_t \tag{1}$$

with $\hat{l}$ representing the credit cycle and $\hat{y}$ the business cycle.

We consider the lagged output gap $\hat{y}_{t-1}$ to tackle the endogeneity problem between the credit cycle and the business cycle, as well as the lagged endogenous variable to allow for a dynamic adjustment.[5] However, since credit market conditions are affected by asset prices and interest rates (see Goodhart and Hofmann (2004), Goodhart and Hofmann (2008), and Bouvatier et al. (2012) among others), credit procyclicality might be overestimated in this specification. From this perspective, Equation (1) can be augmented by the interest rate, as it is standard in the monetary policy literature. We also introduce house and share prices, since there is an obvious link between asset prices dynamics and financial (in)stability: as recalled by Goodhart and Hofmann (2008) among others, booming asset prices episodes are frequently viewed as announcing future sharp correction of prices, generating instability

[5] A second lag on the credit variable is included in the right-hand side of Equation (1) in case of autocorrelation (see below).

of the financial and banking sector. In addition, regarding the interplay between financial constraints and entrepreneurship, both private credit and stock market capitalization can be seen as supplementary (or complementary) sources of financialization. Thus, the linear relationship between aggregate private credit, aggregate economic activity, interest rates and aggregate asset prices can be expressed as follows:

$$\hat{l}_t = \phi_0 + \phi_l \hat{l}_{t-1} + \phi_y \hat{y}_{t-1} + \phi_h \hat{h}_{t-1} + \phi_s \hat{s}_{t-1} + \phi_r \hat{r}_{t-1} + \epsilon_t \tag{2}$$

where $\hat{h}$, $\hat{s}$ and $\hat{r}$ respectively represent the cycle in the house market, the stock market and the interest rate.[6] A potential drawback of the previous equation is that it assumes that both economic expansions and recessions have the same effect (in absolute value) on the credit cycle. Furthermore, a change in output gap of a given magnitude will have the same effect regardless of whether it occurs in a recession or in an expansion state.

To overcome this limit, and in order to investigate potential nonlinearities in the relationship between credit and business cycles, we rely on the STR models developed by Granger and Teräsvirta (1993) and Teräsvirta (1994). These models have several interesting features that make them suitable for our purpose. First, regression coefficients can take different values, depending on the value of another observable variable—namely, the threshold or transition variable. In other words, the observations are divided into a small number of homogenous groups or "regimes", with different coefficients depending on the regimes. Second, regression coefficients are allowed to change gradually when moving from one group to another: STR is a regime-switching model where the transition from one regime to the other is smooth rather than discrete. Finally, countries are allowed to switch between regimes over time according to changes in the threshold variable.

[6] Note that all variables in Equations (1) and (2) are obviously stationary.

More specifically, the STR model can be expressed as follows:[7]

$$\hat{l}_t = \phi_0 + \phi_l \hat{l}_{t-1} + \phi_y \hat{y}_{t-1} + \phi_h \hat{h}_{t-1} + \phi_s \hat{s}_{t-1} + \phi_r \hat{r}_{t-1} + [\phi_0 + \theta_y \hat{y}_{t-1}] \times G(\hat{e}_t; \gamma, c) + \epsilon_t \quad (3)$$

Equation (3) is enlarged with respect to Equation (2) by a transition function, $G(\hat{e}_t; \gamma, c)$, which, in turns, depends on $\hat{e}_t$, an observable transition variable, that governs the regime switching. Note that since our focus is on the effects of booms and busts on the credit cycle, we restrict nonlinearity to the (lagged) output gap (y_{t-1}). This choice has also the advantage of not imposing the same speeds of transition and thresholds to all the variables in Equation (2), an assumption that would be misleading. The transition function can be either a logistic function or a quadratic logistic function and is defined as:

$$G(\hat{e}_t; \gamma, c) = \left[1 + \exp\left(-\gamma \prod_{j=1}^{m} (\hat{e}_t - c_j)\right)\right]^{-1}, \quad \gamma > 0 \quad (4)$$

The transition function is continuous, normalized and bounded between 0 and 1, γ is the slope parameter that determines the smoothness of the transition from one regime to the other, and c denotes the threshold parameter ($c_1 \leq c_2 \leq ... \leq c_m$). Depending on the realization of the transition variable $\hat{e}_t$, the link between $\hat{l}$ and $\hat{y}$ will be specified by a continuum of parameters, namely ϕ_y in Regime 1 (when $G(.) = 0$), and $\phi_y + \theta_y$ in Regime 2, when $G(.) = 1$. In other words, according to the transition variable, output gap has a different impact (elasticity) on credit gap: this model allows us to investigate if nonlinearity in the elasticity could be associated with changes in economic conditions. Indeed, whereas the elasticity in a linear model is constant and equal to ϕ_y in Equation (3), in the STR model the elasticity varies in time according to the value of the transition function. The

[7]The specification is presented with one lag, but the choice of the autoregressive lag is made using information criteria (see below).

two most common cases for the transition function (Equation (4)) correspond to $m = 1$ (logistic, LSTR) and $m = 2$ (quadratic logistic, LSTR2). In the first case, the dynamics is asymmetric and the two regimes are associated with small and large values of the transition variable relative to the threshold. On the contrary, in the case of a quadratic logistic specification, the two regimes have similar structures—meaning that booms and busts have similar dynamics—but the middle grounds are characterized by a different dynamics than that in the extremes.

To specify the STR model, we follow the three-step procedure proposed by Teräsvirta (1994):

- In the first, specification step, we select the autoregressive lag in Equation (3) according to residual properties.
- In the second step, we test the null hypothesis of linearity. Testing this hypothesis consists in testing $\gamma = 0$ in Equation (3). However, Equation (3) being only identified under the alternative hypothesis, this is a nonstandard testing problem. To overcome this issue, we follow Luukkonen et al. (1988) and estimate the auxiliary regression (5) for all the considered transition variables:

$$\hat{l}_t = \beta_0' z_t + \sum_{i=1}^{3} \beta_i' \tilde{z}_t \hat{e}_t^i + u_t \tag{5}$$

where $z_t = (1, \tilde{z}_t)'$, $\tilde{z}_t$ being the vector containing the explanatory variables and the lagged values of the endogenous one.[8] Testing the null hypothesis of linearity in

[8]The auxiliary regression (5) is retained if $\hat{e}_t$ is an element of z_t. If this is not the case, the auxiliary regression takes the following form:

$$\hat{l}_t = \beta_0' z_t + \sum_{i=1}^{3} \beta_i' z_t \hat{e}_t^i + u_t \tag{6}$$

Equation (3) is then equivalent to a test of the hypothesis $H_{00} : \beta_1 = \beta_2 = \beta_3 = 0$ in Equation (5). This test is applied for each considered transition variable. If the null of linearity is rejected for more than one potential transition variable, we then select the transition variable as the variable with the strongest test rejection (i.e. the smallest p-value).

- Once the linearity hypothesis has been rejected, the last step consists in the choice between the LSTR and LSTR2 specifications. To this end, we implement the following test sequence as suggested by Teräsvirta (1994):

  $H_{03} : \beta_3 = 0$

  $H_{02} : \beta_2 = 0|\beta_3 = 0$

  $H_{01} : \beta_1 = 0|\beta_2 = \beta_3 = 0$

  If H_{03} is rejected, the LSTR specification is retained. If H_{03} is accepted and H_{02} is rejected, the LSTR2 model is selected. Finally, not rejecting H_{03} and H_{02}, but rejecting H_{01} leads to the LSTR specification.

Once the choice of the nonlinear specification has been made and the STR model estimated, we apply various misspecification tests: test of no residual autocorrelation (Teräsvirta (1998)), LM-test of no remaining nonlinearity (Eitrheim and Teräsvirta (1996)), ARCH-LM test (Engle (1982)), and normality test (Jarque and Bera (1987)).

3 Data and stylized facts

We consider quarterly data over the 1986-2010 period for the following sample of 17 OECD countries:[9] Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom, and the United States.

As previously mentioned, our analysis is based on the credit cycle and the business cycle—which are our main variables of interest—and three control variables, namely house prices, share prices and the interest rate.

3.1 Credit and business cycles variables

Consider first the credit cycle and business cycle variables. Regarding the credit variable, the series correspond to credit from the banking sector to the private non-financial sector (private credit) taken from the International Financial Statistics (IFS) database of the IMF, except for Canada (source: Statistics Canada), and Norway for 2007Q1 to 2009Q4 (source: Norges Bank). These credit series exhibit important level shifts notably due to changes in definitions. To account for this characteristic, we have adjusted the series for these level shifts following the methodology proposed by Stock and Watson (2003): the growth rate of the observation affected by the level shift is replaced by the median of the growth rate of the two periods before and after the occurrence of the level shift (see also

[9] The starting date of our sample is quite usual in the literature dealing with credit dynamics (see e.g., Goodhart et al. (2004), Jiménez and Saurina (2006), Goodhart and Hofmann (2008) or Bouvatier et al. (2012)). Indeed, it avoids potential biases induced by the major change in the paradigm governing the conduct of monetary policy since the end of the 1970s (Goodhart et al. (2004), and Goodhart and Hofmann (2008)), and corresponds to the end of the high inflation period that characterized the late 1970s and early 1980s.

Goodhart and Hofmann (2008)).[10] In addition, credit aggregates are expressed in real terms considering the consumer price index from the OECD database as deflator. Turning to the GDP series, they are extracted from the OECD database and are expressed in real terms. We derive credit cycle and business cycle variables by isolating the cyclical components of credit and GDP series using the Hodrick-Prescott (HP) filter. The credit cycle is therefore represented by the percentage credit gap (i.e. cyclical component divided by the trend component), and the business cycle by the percentage output gap.[11]

Table 1 presents some descriptive statistics on these percentage credit and output gaps series. Countries are ranking according to the average size of their credit gap measured by the mean of absolute values.[12] Countries recording the more pronounced credit cycle are Sweden, Ireland, Denmark and Spain. The high ranking position of Sweden and Denmark mainly results from the financial cycle encountered by Nordic countries in the turn of the 1990's (Englund (1999), Hansen (2003)). In particular, during the boom period, lending increased by 73% in real terms from 1986 to 1990 in Sweden, and credit growth was 32% in 1986 in Denmark. The high ranking position of Ireland and Spain rather results from the recent period. At the lower ranking position, we find Canada and Germany. The absence of property price boom in Germany during the past decade (Agnello and Schuknecht (2009)) and the implementation of an unweighted leverage ratio since the early 1980's in Canada (Bordeleau et al. (2009)) are two particularities in these countries which could explain the

[10] Following Goodhart and Hofmann (2008), we have corrected for the following level shifts: Australia in 1989Q1 and 2002Q1; Belgium in 1992Q4 and 1999Q1; Canada in 2001Q4; Denmark in 1987Q4, 1991Q1, and 2000Q3; Finland in 1999Q1; France in 1999Q1; Germany in 1990Q2 and 1999Q1; Italy in 1999Q1; Ireland in 1995Q1 and 1999Q1; Japan in 1997Q4 and 2001Q4; Netherlands in 1988Q4; Spain in 1986Q1 and 1999Q1; Sweden in 1996Q1; Switzerland in 1996Q4; UK in 1986Q2; and USA in 2001Q4.

[11] It should be noticed that pre-detrended series obtained with the HP filter might result in data that display spurious business-cycle-like comovements (see Cogley and Nason (1995)). However, as argued by Pedersen (2001) among others, if one defines business cycles in terms of an ideal high pass filter, then the HP filter cannot produce "spurious cycles", because it well approximates an ideal high pass filter. The evidence is then far from conclusive.

[12] The ranking is quite similar if the average size is measured by the standard deviation ($\sigma_{\hat{l}_t}$).

lower size of the credit cycle.

The comparison of credit gaps to output gaps in Table 1 highlights that credit cycle is more pronounced than business cycle. Indeed, the mean and the standard deviation for output gaps are the highest for Finland (respectively at 0.401 and 0.520), while they reach respectively 0.861 and 1.074 for Sweden regarding the credit gap. Furthermore, heterogeneity among countries is more important concerning the credit cycle. The mean for credit gaps ranges between 0.224 in Germany and 0.861 in Sweden, while it ranges between 0.167 in Australia and 0.401 in Finland for output gaps. Credit and business cycles share however a common characteristic concerning persistence; first-order autocorrelations in credit gaps ($\rho_{\hat{l}_t}$) and output gaps ($\rho_{\hat{y}_t}$) being around 0.850 in most countries.

Figure 1 displays the correlations between credit and business cycles in the y-axis and the credit gap size (i.e. the mean on absolute values) in the x-axis. Correlations between the two cycles show an important heterogeneity across countries since they range between 0.103 for Denmark and 0.737 for Switzerland. Moreover, as shown in Figure 1, the correlation is not clearly related to the credit gap size. For example, Sweden and Denmark recorded a pronounced credit cycle but weakly correlated with the business cycle, while Canada and Switzerland faced narrower credit cycles but these swings are highly correlated with the business cycle.

The absence of clear positive correlation between credit and business cycles might hide the existence of nonlinear relationships between the two variables. Indeed, if, for instance, procyclicality becomes more important in times of booms or busts, the previous linear correlations would not be able to capture this pattern. This highlights the importance of allowing for asymmetries in the procyclical character of credit.

3.2 Control and transition variables

Regarding the control variables, the house price series corresponds to the Property Price Index obtained from the Bank for International Settlements (BIS). The interest rate series is the money market rate taken from the OECD database, except for Japan (source: IFS), and Denmark and Finland for which some points were missing for the year 1986 and have been complemented using IFS. Finally, share price series are taken from the OECD database ("all share" prices). As for credit and GDP series, we isolate the cyclical component of our control variables in real terms using the HP filter.[13] More precisely, our interest rate variable is the cyclical component deduced from the HP filter, and our share and house prices variables are the percentage gaps obtained from the HP filter (i.e. cyclical component divided by the trend component).[14]

Finally, we consider five sets of potential transition variables $\hat{e}$:

- The various lagged credit determinants (up to lag 2), corresponding to the credit cycle ($\hat{l}$), the business cycle ($\hat{y}$), share prices ($\hat{s}$), and house prices ($\hat{h}$).
- The lagged values (up to lag 2) of the variable $\hat{e}_1$ corresponding to the first factor of the principal components analysis (PCA) applied to the variables $\hat{y}$ and $\hat{l}$.
- The lagged values (up to lag 2) of the variable $\hat{e}_2$ corresponding to the first factor of the PCA applied to the variables $\hat{y}$ and $\hat{h}$.
- The lagged values (up to lag 2) of the variable $\hat{e}_3$ corresponding to the first factor of the PCA applied to the variables $\hat{y}$ and $\hat{s}$.

[13] See Bouvatier et al. (2012) for a justification of our chosen filtered method to estimate the "equilibrium" value of the interest rate.

[14] It should be noticed that all the filtered series are, by definition, stationary.

- The lagged values (up to lag 2) of the variable $\hat{e}_4$ corresponding to the first factor of the PCA applied to the variables $\hat{h}$ and $\hat{s}$.

Considering this large group of transition variables allows us to account for all possible interactions between the different cycles. Indeed, nonlinearities in credit procyclicality might not be exclusively related to business cycle phases but also to credit, property and stock markets conditions. Examining variables $\hat{l}$, $\hat{h}$ and $\hat{s}$ as potential transition variables therefore allows to identify which cycle is the most appropriate to generate nonlinearities in credit procyclicality. Furthermore, these nonlinearities might also result from the combination of several economic conditions. For example, the effect of the business cycle on the credit cycle could be reinforced when both property and share prices are booming. We therefore use the first factor $\hat{e}_i$ $(i = 1, ..., 4)$ of several PCA, which extracts the main source of variation in the dataset, to identify these features and capture the common pattern in the two cycle variables. For instance, considering $\hat{e}_1$ as the transition variable suggests that credit procyclicality depends on the common pattern shared by business and credit cycles.

4 Results

In order to investigate the potential nonlinear procyclical characteristic of credit, we first test for linearity in Equation (2) using the various transition variables. The results, reported in Table 2, reveal that linearity in the effect of output gap on credit gap cannot be rejected at the 5% significance level in the following countries: Denmark, Germany, Ireland, Italy, Japan, Sweden, and Switzerland. Results from the estimation of the linear equations for these countries are presented in Table 3, which displays the estimates of both Equation (1) (without control variables) and Equation (2) (with control variables).

From these linear estimations, we can distinguish the following situations. In a first group of countries, namely Denmark and Switzerland, output gap does not have a significant effect on credit gap, whatever the considered specification. Turning to the other explanatory variables, share prices significantly affect the credit gap for both countries, as well as the control variables related to interest rates and house prices for Switzerland.

In a second group of countries, namely Germany, Ireland, Sweden and Japan, the impact of output gap differs according to the specification. More precisely, output gap has the expected positive effect for Germany, Ireland, Sweden in the specification without control variables, and becomes non significant in Equation (2). In the case of Germany, our results show counter-cyclical credit dynamics, refuting previous results based on linear specifications (Hofmann (2004)). Striking though these results are, this negative effect in Germany may be explained by the behavior of both households and firms. More specifically, in times of a transitory economic expansion, firms may switch from external to internal finance and thus reduce their borrowing (Bernanke and Gertler (1995)).

Note that in these countries, the original significant impact of output gap in Equation (1) mainly captures the effects of house prices—that are significant in Equation (2)—and not a procyclical characteristic of credit *per se*. The apparent positive relationship between credit and economic activity may thus arise because boom periods trigger increases in property prices which, in turn, affect credit gap. Finally, in the case of Italy, the output gap is an important determinant of credit gap, regardless of the specification.[15]

Turning to the remaining countries for which the linearity hypothesis is rejected, let us first focus on the most appropriate transition variable identified by the Teräsvirta (1994)

[15] Remark that parameter ϕ_y represents the instantaneous effect of output gap on credit gap. The full effect is given by $\phi_y/(1\text{-}\phi_{l,1}\text{-}\phi_{l,2})$.

test. Results in Table 2 display important differences between countries, showing that the economic conditions which lead to nonlinearities in credit cyclicality are heterogeneous. For example, nonlinearities are driven by credit market conditions in Australia, Finland and Spain ($\hat{l}$ is the transition variable), and by property prices in the Netherlands and Norway ($\hat{h}$ is the transition variable). In addition, nonlinearities can result from the combination of different economic conditions. For instance, the variable $\hat{e}_1$—capturing the interdependence between business and credit cycles—is the transition variable for Canada and France. Consequently, the degree of credit procyclicality is modified when output and credit gaps expand or contract simultaneously. On the whole, our findings show that there is no common feature which drives nonlinearities in credit procyclicality; countries particularities regarding the relative importance of credit, property and stock markets can explain this heterogeneity in the selected transition variable.

Results from the estimation of Equation (3) are presented in Table 4.[16] We can distinguish three groups of countries. Firstly, in Finland, the Netherlands, Norway and Spain, the effect of output gap on credit gap decreases when the value of the transition variable increases. These countries are characterized by asymmetries regarding boom and bust periods, with changes in economic activity producing sharp adjustment in bank credit during "bad" times. This effect however tends to dampen during boom periods. In the Netherlands and Spain, the output gap effect reaches respectively 2.148 and 1.714 in bust periods and drops respectively to 0.392 and 0.047 in boom phases.[17]

In Finland and Norway, credit procyclicality is not so high during "bad" times. The output

[16] Standard tests concerning residual properties are also reported in Table 4. In addition, the LM-test of Eitrheim and Teräsvirta (1996) indicate no remaining nonlinearity (the results are available upon request to the authors).

[17] In the LSTR model, the effect of output gap on credit gap is given by ϕ_y in bust periods, and by $\phi_y + \theta_y$ in boom periods, representing the two extreme situations. In addition, recall that the link between credit and output gaps is specified by a continuum of parameters, with the elasticity varying in time according to the value of the transition function.

gap effect ranges respectively from 0.269 and 0.180 to -0.069 and -0.341. Credit procyclicality turns non significant during boom phases in Spain and Finland and credit becomes even countercyclical in Norway. Furthermore, the threshold parameter (c_1) and the slope parameter (γ) indicate differences in the smoothness of the transition between the two extreme regimes.[18] Whereas the previous literature based on linear estimations (e.g. Hofmann (2004)) show procyclical credit in Finland, Spain, Netherlands and Norway, they fail to capture the asymmetric effect in times of booms and busts. Our results underscore the importance of correctly specifying the nonlinear effects under scrutiny.

Figure 2 depicts the transition function according to the value taken by the transition variable, which illustrates more precisely the transition between the two regimes. In the Netherlands, the threshold parameter ($c_1 = -0.507$) is low comparing to Spain, Finland and Norway for which this coefficient is respectively 0.158, 0.327 and 1.243. The Netherlands have also the highest slope parameter. As a result, the very high credit procyclicality captured by $\phi_y = 2.148$ characterizes few data points. The opposite situation is observed for Norway, while the repartition between the two regimes is more balanced for Spain and Finland. Figure 3 displays the time path of the transition function and therefore allows to identify periods of high or low credit procyclicality. For instance, output gap sharply affects credit gap in Spain after the 1992-3 European Monetary System crisis or after the 2007-9 financial crisis. The fall in the positive effect of output gap on credit gap when the economy turns in a boom period suggests that the other significant determinants of the credit cycle become relatively more prominent.

According to our results, property prices in Finland and the Netherlands, share prices in

[18] However, it would be a mistake to judge the significance of these variables by means of its t-values. In fact, as noticed by Terasvirta (1994), their t-statistics do not have their customary asymptotic t-distribution under the hypothesis that $\gamma = 0$ and $c_j = 0$, due to identification problems.

Norway, and these two price series in Spain might be more relevant to explain short-run credit dynamics than economic activity itself in boom periods for several reasons. First of all, property accounts for a substantial share of household assets, so that changes in property prices in boom periods may have a significant wealth effect on credit demand. Second, rapid increases in house or share prices rise the availability of funds for those that can pledge them as collateral (Jiménez and Saurina (2006)), affecting the borrowing capacity of the private sector. Finally, increases in the value of assets that can serve as collateral make banks more willing to extend loans, so that the supply of credit to the private sector also increases (Hofmann (2004)).

In a second group of countries, namely, Australia, Belgium and France, the effect of output gap on credit gap decreases in boom periods, as in the previous group, but also during bust phases. Nonlinearities are therefore represented by a quadratic logistic transition function (LSTR2), implying that credit procyclicality in booms and busts is characterized by similar dynamics. Any increase or decrease in output gap has a relatively higher impact on credit in "normal" times (i.e. periods which are neither booms nor busts) than during "extreme" periods. Credit procyclicality in normal times, given by parameter ϕ_y, is 0.544 in Australia, 0.810 in Belgium and 0.909 in France. Considering parameters $\phi_y + \theta_y$, this effect turns non significant in Belgium and France during extreme periods, and credit gap becomes even countercyclical in Australia. In these countries, factors such as house and share prices play a greater role during the extreme states, putting forward the prevalence of the financial factors over real ones during boom and bust periods.

More precisely, credit gaps are significantly impacted by property prices in Australia and Belgium, while the three control variables are not significant in France. In this latter case, credit gap becomes highly counter-cyclical during extreme periods. We have to be cautious concerning the similar dynamics in booms and busts obtained with the LSTR2 model. The threshold parameters c_1 and c_2 and Figure 2 show that the reduction of credit procyclicality concerns rather bust periods than booms. Indeed, parameters c_2 are relatively high and then few data points are classified in the extreme regime when the transition variable is positive. Finally, it is worth mentioning that Australia, Belgium and France share a characteristic with the previous group of countries. Credit procyclicality is significant when the transition variable is around zero, i.e. when the economy is not in bust or boom periods. In extreme periods, output gap is not necessary a significant determinant of credit gap.

In the last group of countries, namely, Canada, the United States and the United Kingdom, nonlinearities are also represented by a quadratic logistic transition function. However, contrary to the previous group, procyclicality becomes more important both in boom and bust periods. More precisely, the output gap effect on credit gap in normal periods—measured by parameter ϕ_y—is not significant for Canada and the United States. The size of this effect during extreme periods (given by $\phi_y + \theta_y$) rises and becomes significant. It reaches 0.374 in Canada and 0.413 in the United States. It is important to remark that our estimations yield higher cyclicality in extreme periods, advancing that previous studies based on linear estimations may have underestimated the real impact of the economic cycle. Our results showing asymmetric cyclicality may have important policy implications in terms of regulation.

Finally, concerning the United Kingdom, the output gap effect is always significant and increases from 0.879 in normal times to 0.989 in extreme periods. It is worth mentioning that in this country, extreme periods correspond to very rare events, suggesting that the nonlinearity is caused just by a few points (see Figures 2 and 3). The transitions between the two regimes are more frequent for Canada and the United States.

5 Conclusion

Many industrialized countries experienced high credit expansion before the recent financial turmoil, putting forward that understanding the mechanism underlying credit constitutes an important challenge. Focusing on one of its main determinants in a short-run perspective, this paper examines the link between output gap and credit gap in a nonlinear framework for 17 OECD countries over the 1986-2010 period. Relying on smooth transition regression models, we show that economic activity nonlinearly affects credit, in the sense that output gap does not impact credit gap in the same magnitude depending on economic conditions. More generally, our findings highlight that the cyclical character of credit depends on whether the economy undergoes a boom, a bust or is in a "normal" configuration. This result has important implications in terms of regulation, for instance to identify which regulatory instrument is appropriate to curb bank lending.

More specifically, our findings show that different dynamics can be distinguished. Firstly, we identify countries in which the effect of output gap on credit gap tends to dampen during booms and also possibly during busts. In these countries—namely, Australia, Belgium, France, Finland, the Netherlands, Norway, and Spain—asset prices prevail over economic activity during some "extreme" states in the short-run dynamics of bank credit. Secondly, the opposite dynamics can be found in Canada, the United Kingdom and the United States. For these economies, procyclical effects are mild in "normal" periods and reach their maximum during boom and bust phases. Thirdly, the output gap does not seem to be a significant determinant of credit gap in Denmark, Germany, Ireland, Japan, Sweden and Switzerland, whatever the economic conditions. Finally, we find differences between countries concerning the transition variable and the threshold parameters, suggesting that the definition of "extreme" periods results from countries particularities.

This heterogeneity across both countries and regimes puts forward that there does not exist a "one size fits all" policy or recommendation, even at the European level. Large output gaps are not necessarily costly in terms of credit cyclicality in the sense that the effect of the business cycle on credit cycle can dampen during boom and bust phases. Furthermore, in many cases, the short-run bank credit behavior is mainly driven by other variables than the business cycle, such as financial assets. Indeed, in addition to the wealth effect on credit demand exerted by rising property prices, house and asset prices probably serve as a collateral in booming periods, making banks more willing to extend loans and leading to an increase in the supply of credit to the private sector. On the whole, our findings show that understanding and assessing the short-run dynamics of bank credit is a rather difficult task that requires paying a particular attention not only to the economic activity, but also to financial factors.

A large set of macro-prudential policy tools appropriate to curb the credit cycle has been highlighted following the recent financial crisis. Macro-prudential instruments included in Basel 3 proposals, as for example the leverage ratio or the countercyclical capital buffer, focus on banks' balance sheets in order to affect credit supply. However, some other macro-prudential policy tools propose to address directly the sources of financial imbalances (ECB (2010)). For instance, imposing limits on loan-to-value or loan-to-income ratios could be appropriate to curb credit during the build-up of financial imbalances. These regulatory instruments could focus on a specific credit market segment or a specific category of banks' customers. As a result, activating a home-loan-to-value ratio when property market are overheated could be relevant if property prices are an important driver of the credit cycle during boom periods. The adoption of complementing measures to Basel 3 proposals could be possible at the European Union level. Indeed, the European Systemic Risk Board (ESRB) will have to support the improvment of the macro-prudential framework if the banking sector is not resilient to financial imbalances.

References

Agnello, L. and Schuknecht, L. 2009. Booms and busts in housing markets - determinants and implications. Working Paper Series 1071, European Central Bank.

Aikman, D., Haldane, A., and Nelson, B. 2011. Curbing the credit cycle. New York, Columbia University Center on Capitalism and Society Annual Conference.

Bordeleau, E., Crawford, A., and Graham, C. 2009. Regulatory constraints on bank leverage: Issues and lessons from the canadian experience. Discussion Papers 09-15, Bank of Canada.

Borio, C. and Drehmann, M. 2009. Assessing the risk of banking crises - revisited. *BIS Quarterly Review*, (March 2009):29–46.

Borio, C., Furfine, C., and Lowe, P. 2001. Procyclicality of the financial system and financial stability: issues and policy options. BIS Papers 1, Bank for International Settlements.

Bouvatier, V., López-Villavicencio, A., and Mignon, V. 2012. Does the banking sector structure matter for credit procyclicality? *Economic Modelling*, 29:1035–1044.

Calza, A., Gartner, C., and Sousa, J. 2003. Modelling the demand for loans to the private sector in the euro area. *Applied Economics*, 35(1):107–117.

Calza, A., Sousa, J., and Manrique, M. 2006. Credit in the euro area: An empirical investigation using aggregate data. *The Quarterly Review of Economics and Finance*, 46(2):211–226.

Cogley, T. and Nason, J. M. 1995. Effects of the hodrick-prescott filter on trend and difference stationary time series implications for business cycle research. *Journal of Economic Dynamics and Control*, 19(1-2):253–278.

ECB 2010. Macro-prudential policy objectives and tools. *European Central Bank - Financial Stability Review*, (June 2010):129–137.

Eitrheim, O. and Teräsvirta, T. 1996. Testing the adequacy of smooth transition autoregressive models. *Journal of Econometrics*, 74:59–76.

Eller, M., Frömmel, M., and Srzentic, N. 2010. Private sector credit in cesee: Long-run relationships and short-run dynamics. *Focus on European Economic Integration*, (2):50–78.

Engle, R. 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. *Econometrica*, 50:987–1007.

Englund, P. 1999. The swedish banking crisis: Roots and consequences. *Oxford Review of Economic Policy*, 15(3):80–97.

Frömmel, M. and Schmidt, T. 2006. Bank lending and asset prices in the euro area. RWI Discussion Papers 0042, Rheinisch-Westfälisches Institut für Wirtschaftsforschung.

Gambacorta, L. and Rossi, C. 2010. Modelling bank lending in the euro area: a nonlinear approach. *Applied Financial Economics*, 20(14):1099–1112.

Goodhart, C. and Hofmann, B. 2004. Deflation, credit and asset prices. In *Deflation. Current and Historical Perspectives, R. Burdekin and P. Siklos (eds)*. Cambridge University Press.

Goodhart, C. and Hofmann, B. 2008. House prices, money, credit, and the macroeconomy. *Oxford Review of Economic Policy*, 24(1):180–205.

Goodhart, C., Hofmann, B., and Segoviano, M. 2004. Bank regulation and macroeconomic fluctuations. *Oxford Review of Economic Policy*, 20(4).

Gorton, G. and He, P. 2008. Bank credit cycles. *The Review of Economic Studies*, 75:1181–1214.

Granger, C. and Teräsvirta, T. 1993. *Modeling Nonlinear Economic Relationships*. Oxford: Oxford University Press.

Hansen, J. 2003. Financial cycles and bankruptcies in the nordic countries. Working Paper Series 149, Sveriges Riksbank (Central Bank of Sweden).

Hofmann, B. 2004. The determinants of bank credit in industrialized countries: Do property prices matter? *International Finance*, 7(2):203–234.

Jarque, C. and Bera, A. 1987. A test for normality of observations and regression residuals. *International Statistical Review*, 55:163–172.

Jiménez, G. and Saurina, J. 2006. Credit cycles, credit risk, and prudential regulation. *International Journal of Central Banking*, 2(2).

Kakes, J. 2000. *Monetary Transmission in Europe: the Role of Financial Markets and Credit*. Edward Elgar, Cheltenham.

Laeven, L. and Valencia, F. 2011. The real effects of financial sector interventions during crises. IMF Working Papers 11/45, International Monetary Fund.

Luukkonen, R., Saikkonen, P., and Teräsvirta, T. 1988. Testing linearity against smooth transition autoregressive models. *Biometrika*, 75:491–499.

Pedersen, T. M. 2001. The hodrick-prescott filter, the slutzky effect, and the distortionary effect of filters. *Journal of Economic Dynamics and Control*, 25(8):1081–1101.

Stock, J. and Watson, M. 2003. Forecasting output and inflation: The role of asset prices. *Journal of Economic Literature*, 41:788–829.

Teräsvirta, T. 1994. Specification, estimation and evaluation of smooth transition autoregressive models. *Journal of the American Statistical Association*, 89:208–218.

Teräsvirta, T. 1998. Modeling economic relationships with smooth transition regressions. *in: Handbook of Applied Statistics.*

White, W. R. 2006. Procyclicality in the financial system: do we need a new macrofinancial stabilisation framework? BIS Working Papers 193, Bank for International Settlements.

Table 1: Descriptive statistics: credit gap and output gap

	Credit gap ($\hat{l}_t$)				Output gap ($\hat{y}_t$)			
	Mean	$\sigma_{\hat{l}_t}$	$\rho_{\hat{l}_t}$	Min / Max	Mean	$\sigma_{\hat{y}_t}$	$\rho_{\hat{y}_t}$	Min / Max
Sweden	0.861	1.074	0.888	-2.094 / 2.402	0.270	0.349	0.858	-0.815 / 0.810
Ireland	0.777	0.900	0.921	-1.676 / 1.950	0.349	0.434	0.808	-0.992 / 1.220
Denmark	0.770	1.001	0.804	-1.875 / 3.670	0.229	0.291	0.804	-0.812 / 0.625
Spain	0.643	0.728	0.919	-1.536 / 1.125	0.209	0.259	0.842	-0.495 / 0.736
Belgium	0.520	0.651	0.823	-1.485 / 1.633	0.191	0.234	0.832	-0.475 / 0.485
Finland	0.519	0.639	0.897	-1.383 / 1.316	0.401	0.520	0.908	-1.006 / 1.357
United Kingdom	0.490	0.629	0.876	-0.936 / 1.842	0.207	0.274	0.920	-0.601 / 0.605
United States	0.476	0.591	0.931	-1.295 / 1.264	0.178	0.219	0.879	-0.525 / 0.466
Italy	0.453	0.547	0.739	-1.071 / 1.353	0.193	0.241	0.881	-0.592 / 0.555
France	0.446	0.522	0.878	-0.819 / 1.261	0.178	0.214	0.904	-0.385 / 0.455
Norway	0.417	0.476	0.889	-0.764 / 0.893	0.188	0.237	0.452	-0.625 / 0.533
Switzerland	0.386	0.472	0.791	-0.721 / 1.159	0.210	0.258	0.903	-0.442 / 0.704
Australia	0.320	0.396	0.782	-0.743 / 1.082	0.167	0.216	0.844	-0.488 / 0.552
Japan	0.314	0.384	0.781	-0.902 / 0.752	0.262	0.324	0.793	-1.091 / 0.628
Netherlands	0.310	0.403	0.808	-1.187 / 1.166	0.214	0.260	0.879	-0.534 / 0.719
Canada	0.268	0.330	0.911	-0.492 / 0.917	0.231	0.281	0.907	-0.553 / 0.576
Germany	0.224	0.278	0.773	-0.513 / 0.681	0.243	0.302	0.804	-0.691 / 0.852

Note: Means are computed on absolute values.

Table 2: Linearity tests

Country	Transition variable				Linearity test (Teräsvirta, 1994)				Conclusion
	Name	Min	Max	SD	H_{00}	H_{03}	H_{02}	H_{01}	
Australia	$\hat{l}_{t-2}$	-0.74	1.08	0.39	0.0141	0.1070	0.0080	0.3250	LSTR2
Belgium	$\hat{y}_{t-2}$	-0.48	0.49	0.23	0.0185	0.2000	0.0039	0.6430	LSTR2
Canada	$\hat{e}_{1,t-2}$	-2.24	3.41	1.30	0.0354	0.1070	0.0166	0.6700	LSTR2
Denmark	$\hat{y}_{t-2}$	-0.69	0.63	0.27	0.0975	0.4850	0.1070	0.0861	Linear
Finland	$\hat{l}_{t-2}$	-1.38	1.32	0.63	0.0157	0.0097	0.1240	0.3560	LSTR
France	$\hat{e}_{1,t-2}$	-1.81	3.29	1.30	0.0286	0.6070	0.0188	0.0724	LSTR2
Germany	$\hat{s}_{t-1}$	-10.79	7.06	3.59	0.0759	0.1060	0.0410	0.7900	Linear
Ireland	$\hat{s}_{t-1}$	-10.90	7.91	3.32	0.2100	0.7020	0.0366	0.9390	Linear
Italy	$\hat{e}_{4,t-2}$	-2.08	2.27	0.95	0.0501	0.2620	0.0178	0.3990	Linear
Japan	$\hat{y}_{t-2}$	-1.09	0.63	0.32	0.1490	0.5440	0.1600	0.0971	Linear
Netherlands	$\hat{h}_{t-1}$	-1.11	0.94	0.40	0.0115	0.0068	0.0628	0.6750	LSTR
Norway	$\hat{h}_{t-2}$	-2.38	1.97	0.98	0.0189	0.2210	0.0764	0.0284	LSTR
Spain	$\hat{l}_{t-1}$	-1.54	1.13	0.71	$6.97 \text{x} 10^{-6}$	0.6010	0.0678	$1.37 \text{x} 10^{-6}$	LSTR
Sweden	$\hat{e}_{1,t-2}$	-2.48	2.43	1.15	0.2200	0.3590	0.1550	0.2890	Linear
Switzerland	$\hat{e}_{1,t-2}$	-2.21	3.45	1.34	0.0758	0.0443	0.1270	0.6180	Linear
UK	$\hat{e}_{2,t-2}$	-2.51	3.58	1.33	0.0247	0.4070	0.0099	0.1720	LSTR2
USA	$\hat{s}_{t-2}$	-6.53	4.32	2.02	0.0157	0.1820	0.0111	0.1960	LSTR2

Note: The table displays p-values associated with hypotheses H_{00}, H_{03}, H_{02} and H_{01} for the transition variable with the strongest test rejection (i.e. the smallest p-value). The minimum, maximum and standard deviation (SD) of the transition variable are also reported.

Table 3: Linear model

	Denmark		Germany		Ireland		Italy		Japan		Sweden		Switzerland	
$\phi_{l,1}$	0.629^a	0.570^a	0.761^a	0.645^a	0.843^a	0.782^a	0.507^a	0.497^a	0.791^a	0.674^a	0.839^a	0.666^a	0.666^a	0.498^a
	(5.84)	(5.79)	(12.18)	(9.27)	(16.74)	(17.75)	(4.81)	(4.39)	(11.88)	(9.40)	(18.42)	(8.58)	(6.53)	(5.27)
$\phi_{l,2}$	0.170	0.234^b					0.335^a	0.374^a					0.276^a	0.335^a
	(1.54)	(2.31)					(3.38)	(3.47)					(2.96)	(3.49)
ϕ_y	0.044	-0.311	0.106^a	-0.161^b	0.282^b	0.136	0.322^b	0.479^b	-0.025	-0.157^c	0.486^b	-0.176	-0.236	-0.123
	(0.20)	(-1.02)	(2.66)	(-2.09)	(2.54)	(1.26)	(2.48)	(2.13)	(-0.35)	(-1.73)	(2.59)	(-0.45)	(-1.37)	(-0.74)
ϕ_h		0.019		0.130^b		0.146^a		0.011		0.117		0.373^a		0.153^a
		(0.25)		(2.19)		(3.21)		(0.21)		(1.27)		(2.69)		(4.64)
ϕ_s		0.080^a		0.004		0.002		-0.002		0.030^a		0.013		0.031^a
		(3.41)		(0.92)		(0.16)		(-0.24)		(3.44)		(0.65)		(3.41)
ϕ_r		-0.041		0.094^a		-0.034		-0.061		-0.018		-0.002		-0.067^b
		(-0.09)		(2.80)		(-1.63)		(-1.14)		(-0.34)		(-0.04)		(-2.38)
ϕ_0	-0.023	-0.014	0.004	0.003	-0.001	0.010	-0.002	0.001	0.006	0.003	-0.003	0.011	-0.009	-0.015
	(-0.35)	(-0.25)	(0.28)	(0.21)	(-0.04)	(0.28)	(-0.05)	(0.01)	(0.30)	(0.17)	(-0.07)	(0.25)	(-0.29)	(-0.57)
$AR(1)test$	5.588	3.586	0.497	0.590	1.117	0.021	0.187	0.100	0.001	0.030	0.204	0.007	5.440	0.001
$[p-value]$	[0.020]	[0.061]	[0.482]	[0.444]	[0.293]	[0.883]	[0.665]	[0.752]	[0.975]	[0.862]	[0.652]	[0.931]	[0.021]	[0.974]
$AR(2)test$	6.610	2.380	0.335	0.299	4.425	2.344	3.034	1.976	1.658	1.946	0.526	0.129	3.607	0.235
$[p-value]$	[0.002]	[0.098]	[0.715]	[0.741]	[0.014]	[0.101]	[0.053]	[0.144]	[0.196]	[0.148]	[0.592]	[0.878]	[0.031]	[0.790]
$ARCHtest$	1.100	2.251	2.870	1.764	6.232	5.829	0.480	0.658	1.223	2.305	0.842	1.288	0.031	0.232
$[p-value]$	[0.337]	[0.111]	[0.061]	[0.177]	[0.002]	[0.004]	[0.619]	[0.520]	[0.298]	[0.105]	[0.433]	[0.280]	[0.968]	[0.793]
$JB\ test$	19.215	3.093	0.456	0.774	1.696	3.136	2.008	0.511	0.480	2.039	1.865	3.377	3.761	1.446
$[p-value]$	[0.001]	[0.212]	[0.795]	[0.678]	[0.428]	[0.208]	[0.366]	[0.774]	[0.786]	[0.360]	[0.393]	[0.184]	[0.152]	[0.485]
$\bar{R}^2$	0.712	0.761	0.612	0.744	0.842	0.860	0.649	0.648	0.619	0.648	0.821	0.841	0.698	0.744

Note: a, b and c indicate significance respectively at the 1%, 5% and 10% levels. T-stat are in brackets and are computed from Newey-West robust standard errors. A dummy variable is included in 1986q4 for Denmark, 1993q1 for Germany, 1991q4 for Ireland, 1989q4 for Italy and 2001q1 for Switzerland.

Table 4: STR model

	Australia	Belgium	Canada	Finland	France	Netherlands	Norway	Spain	UK	USA
Linear part										
$\phi_{l,1}$	0.451^{a} (4.82)	0.698^{a} (9.18)	1.105^{a} (11.42)	0.762^{a} (11.34)	0.603^{a} (9.68)	0.610^{a} (7.77)	0.785^{a} (17.81)	0.179^{c} (1.86)	0.415^{a} (4.20)	0.769^{a} (6.87)
$\phi_{l,2}$	0.310^{a} (3.46)		-0.342^{a} (-3.61)					0.352^{a} (4.58)	0.185^{b} (2.15)	-0.131 (-1.38)
ϕ_y	0.544^{a} (4.07)	0.810^{a} (2.82)	0.029 (0.36)	0.269^{c} (1.89)	0.909^{a} (4.19)	2.148^{a} (3.68)	0.180^{b} (1.96)	1.714^{a} (6.21)	0.879^{a} (5.55)	0.216 (0.86)
ϕ_h	0.072^{b} (2.48)	0.232^{c} (1.89)	0.006 (0.26)	0.062^{b} (2.12)	0.076 (1.49)	0.206^{a} (2.89)	0.013 (0.50)	0.127^{a} (3.82)	-0.056 (-1.12)	0.128^{c} (1.71)
ϕ_s	0.010 (1.14)	0.013 (1.02)	0.020^{a} (3.33)	-0.006 (-0.69)	0.011 (1.30)	-0.005 (-0.47)	0.022^{a} (3.81)	0.025^{a} (3.16)	-0.026^{c} (-1.97)	0.006 (0.432)
ϕ_r	-0.004 (-0.22)	-0.019 (-0.39)	-0.021 (-1.50)	-0.022 (-0.72)	0.050 (1.52)	-0.045 (-1.10)	0.020 (1.42)	-0.004 (-0.21)	0.047^{c} (1.73)	0.077^{b} (2.43)
ϕ_0	0.008 (0.40)		0.004 (0.38)		-0.054^{c} (-1.89)	-0.004 (-0.20)			-0.033 (-1.29)	-0.102^{b} (-2.15)
Nonlinear part	LSTR2	LSTR2	LSTR2	LSTR	LSTR2	LSTR	LSTR	LSTR	LSTR2	LSTR2
θ_y	-0.951^{a} (-3.85)	-1.024^{a} (-2.90)	0.345^{a} (2.71)	-0.338^{b} (-2.49)	-0.747^{b} (-2.56)	-1.756^{a} (-3.05)	-0.521^{b} (-2.43)	-1.667^{a} (-5.00)	0.110 (0.44)	0.196 (0.75)
θ_0		-0.122^{b} (-2.19)		0.123^{c} (1.65)			0.136^{b} (2.14)	0.244^{a} (3.32)	0.539^{a} (4.31)	0.170^{a} (3.00)
γ	112.179	66.235	6.319	10.121	79.884	25.013	7.120	5.180	54.397	29.289
c_1	-0.477	0.070	-1.429	0.327	-0.278	-0.507	1.243	0.158	-2.230	-0.312
c_2	0.841	0.423	2.104		2.818				2.802	1.420
$\theta_y + \phi_y$	-0.407^{c} (-1.89)	-0.214 (-0.80)	0.374^{a} (2.73)	-0.068 (-0.54)	0.162 (0.74)	0.392^{b} (2.09)	-0.341^{c} (-1.79)	0.047 (0.19)	0.989^{a} (4.01)	0.413^{b} (2.26)
$AR(1)test$ [$p-value$]	2.154 [0.145]	1.250 [0.266]	1.912 [0.170]	0.821 [0.367]	3.807 [0.054]	1.333 [0.251]	0.741 [0.391]	0.853 [0.358]	0.319 [0.573]	0.268 [0.605]
$AR(2)test$ [$p-value$]	1.361 [0.262]	1.266 [0.287]	4.312 [0.016]	0.450 [0.638]	2.292 [0.107]	0.668 [0.515]	0.586 [0.558]	0.339 [0.713]	0.188 [0.828]	0.169 [0.844]
$ARCHtest$ [$p-value$]	0.177 [0.949]	1.129 [0.347]	2.411 [0.055]	0.139 [0.869]	2.070 [0.132]	1.556 [0.216]	2.982 [0.055]	0.170 [0.843]	0.172 [0.842]	0.427 [0.653]
$JB\ test$ [$p-value$]	0.207 [0.901]	0.984 [0.611]	0.686 [0.611]	7.671 [0.021]	4.642 [0.098]	4.261 [0.118]	2.258 [0.323]	1.211 [0.545]	0.056 [0.972]	0.541 [0.763]
$\bar{R}^2$	0.787	0.775	0.901	0.849	0.873	0.694	0.907	0.921	0.875	0.896

Note: a, b and c indicate significance respectively at the 1%, 5% and 10% levels. T-stat are in brackets. A dummy variable in included in 1988q4 for Australia, 1990q1 for Belgium and 1992q4 for France.

Figure 1: **Credit and business cycles correlation**

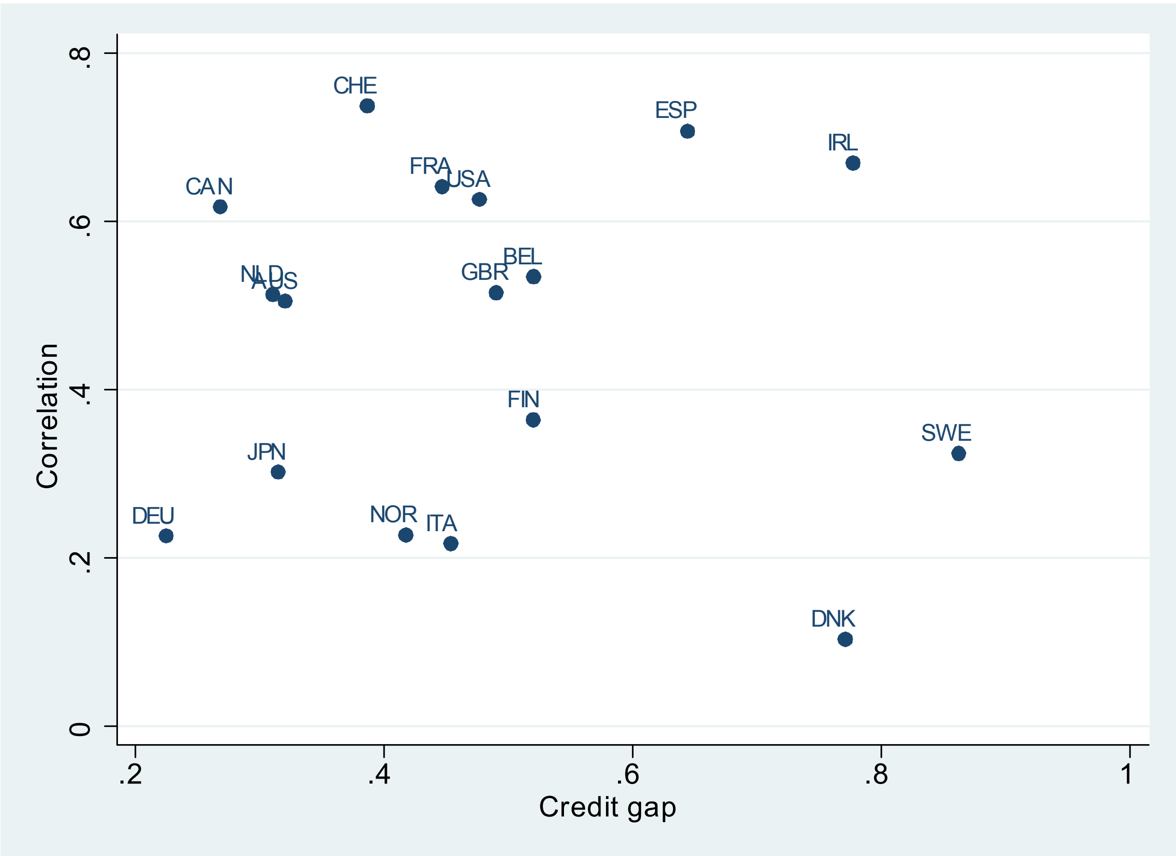

Figure 2: **Transition function vs transition variable**

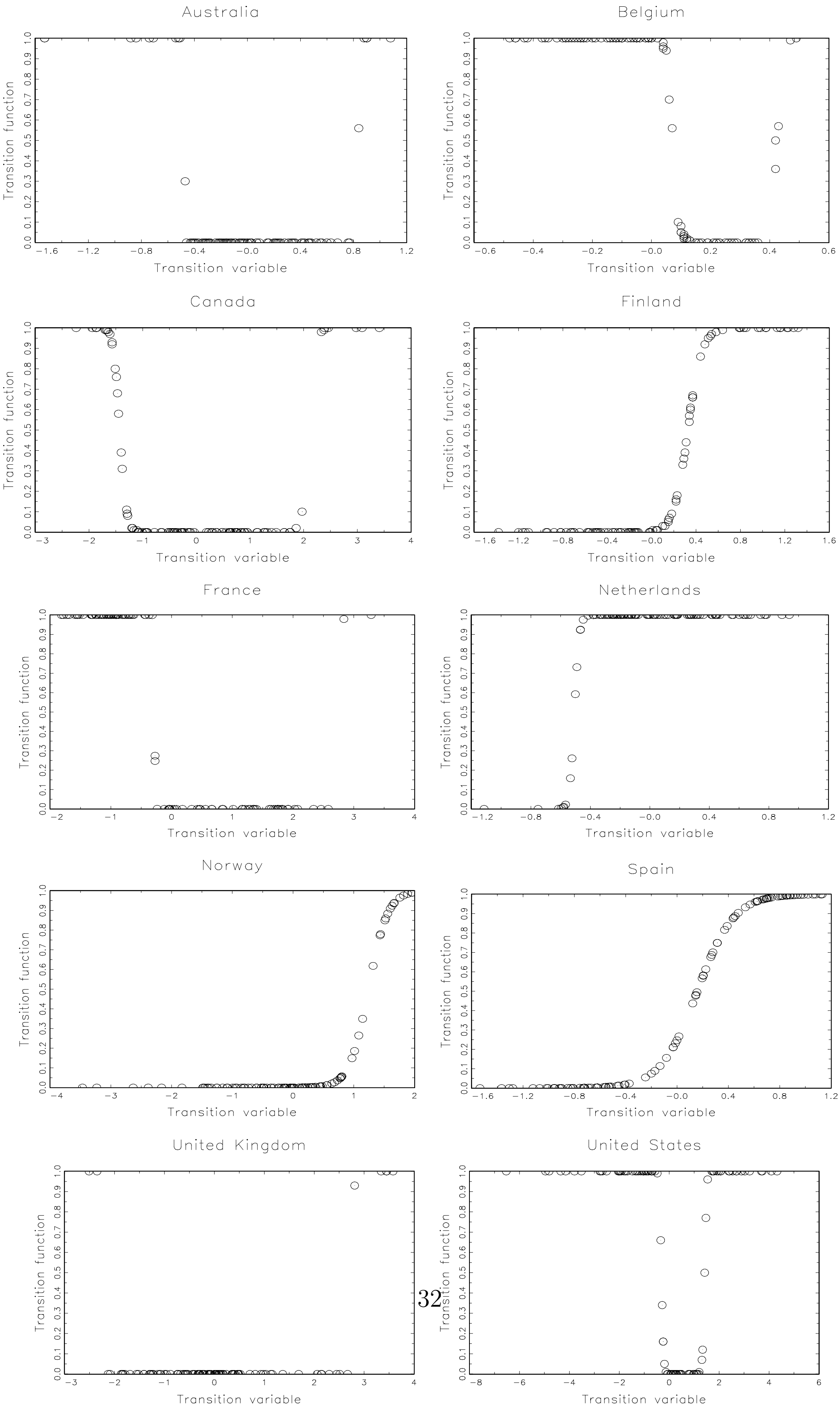

Figure 3: **Transition function in time**