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GOOD TIMES AND CRISIS.

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Résumé Cet article propose un modèle parcimonieux pour expliquer et prévoir les crédits bancaires aux entreprises non financières en France, en régime de croissance, ainsi qu'en situation de crise. Ce faisant, nous sommes amenés à évaluer le contenu en information d'indicateurs simples et étudions la dynamique potentiellement non-linéaire du crédit. Nous trouvons que le taux de croissance des cours boursiers est un des indicateurs avancés les plus performants. Ceci s'explique théoriquement par des effets de bilan. De plus, nous trouvons que les cours boursiers constituent une variable de seuil pertinente pour expliquer des changements de régime dans l'évolution du crédit. Cependant, il s'avère difficile de les prévoir avec précision. C'est pourquoi un simple modèle VAR linéaire présente somme toute de meilleures performances prédictives.

Mots-clés : Crédit, Prévision, VECM, VAR à changements de régime, Indicateurs avancés

Codes JEL : E51, E47, C22

Abstract This paper aims to develop a parsimonious model to explain and forecast bank loans to non-financial companies during calm periods as well as in situations of financial turmoil. In doing so, we are led to gauge the marginal informational content of simple leading indicators, and to investigate potential non-linearity in credit dynamics. This framework is applied to the French context, over a period including financial, banking and sovereign debt crises. In accordance with firms and banks' balance sheets effects, the growth rate of equity prices appears to be one of the most interesting leading indicator as well as a significant threshold variable for explaining regime switching. However, our results highlight the difficulties to accurately predict the right credit dynamics regimes. A simple VAR model finally performs better.

Keywords: Credit, Forecast, VECM, Threshold VAR, leading indicators

JEL Classification: E51, E47, C22

Non-technical summary

The successive financial, banking and sovereign debt crises had huge effects on banking credit, especially in Europe. In France, for instance, the flow of bank loans to non-financial firms as a share of GDP decreased by 145 percentage points from mid-2007 to the second quarter of 2009. In a country where small and medium sized enterprises are prevalent, and where roughly two thirds of total non-financial corporate financing is made of bank loans, such a credit collapse had in turn a significant negative impact on economic activity.

This context is reviving research on credit. The recent literature, mainly empirical, generally seeks to find how the credit market has passed the financial shocks on to the real sector. Related papers mainly focus on bank lending rates or on interest rate spreads, while neglecting the flow of loans. Economists, central banks and international institutions did not expect the credit collapse in the wave of the financial crisis. That is why an update of the empirical methods and of the key determinants to consider for explaining and forecasting credit are required.

The objective of this paper is precisely to develop a parsimonious model for explaining and forecasting credit, while gauging the marginal informational content of some simple leading indicators. Additionally, we investigate non-linearity in credit dynamics, having in mind that bank loans activity can change depending on the financial context. Our contribution is original too in that it is applied to the French context, which has been ignored so far in the literature. Last, this analysis deals with a period combining both good times and (financial, banking and sovereign) crises.

First, we find that a simple Vector Error Correction Model (VECM) with explicit long-run supply and demand relationships for loans, which is relevant for other European countries according to the existing literature, is acceptable for explaining credit dynamics in France as well. However, we show that a simple Vector Auto-Regressive (VAR) model provides more accurate loan forecasts. Next, we investigate the marginal predictive power of a large set of (more than 40) indicators, like banks lending survey indicators, asset prices, interest rates spreads, indicators of risk, banks' balance sheet ratios, policy variables, etc. More precisely, we gauge whether they allow for improving the loan's forecast accuracy of the aforementioned baseline VAR model.

We find that equity prices are one of the most relevant leading indicators of bank loans. This can be theoretically justified. Stock prices represents for future cash flow, a fair proxy of the borrowers' balance-sheet quality according to the literature on the financial accelerator. The lower the equity prices, the higher the external financial premium that firms must bear and hence the lower their borrowing capacity. Moreover, any change in equity prices affects both the liability and the asset side of banks' balance sheets. According to the bank capital channel theory, any decline in asset prices depreciates the value of banks' securities portfolio and decreases their retained earnings. The resulting fall in their own equity capital leads the banks to tighten credit conditions and/or to diminish credit supply.

These theories describe nonlinear mechanisms. We have therefore considered switching regimes in credit dynamics, depending on the evolution of equity prices. Tests and estimations based on a Threshold VAR (TVAR) model confirm that the growth rate of the CAC40 constitutes a significant transition variable for explaining shifts in credit dynamics. However, concerning forecast accuracy, the TVAR model is not significantly better than the VAR model augmented with equity prices. Indeed, the nonlinear model fails to accurately predict the right regime (i.e. to forecast the threshold variable); forecasting errors when the regime is incorrectly predicted can be important, so much so that a simple linear VAR model finally performs better than more sophisticated models.

1 Introduction

The successive financial, banking and sovereign debt crisis had huge effects on banking credit, especially in Europe. In France, for instance, the flow of bank loans to non-financial firms as a share of GDP decreased by 145 percentage points from mid-2007 to the second quarter of 2009[1]. In a country where small and medium sized enterprises (SMEs) are prevalent, and where roughly two thirds of total non-financial corporate financing is made of bank loans, such a credit collapse had in turn a significant negative impact on economic activity[2]. More than 6 years since the financial crisis began, credit remains a source of concern. In its Global Financial Stability Report of April 2014, the IMF highlighted that "*without a flow of new credit, it will be difficult for the euro area to complete its transition from financial fragmentation to integration*". However, large European Union banks have continued to deleverage, reducing assets by $2.5 trillion over 2011-2014. Moreover, they are still restructuring their balance-sheets, by substituting capital-intensive businesses and increasing the share of low risks-weighted assets.

This context is reviving research on credit. The recent literature, mainly empirical, generally seeks to find how the credit market has passed the financial shocks on to the real sector[3]. Related papers did not intend to develop macro-econometric models for explaining and forecasting credit. Yet, the financial crisis revealed shortcomings on this point. Typically, the credit collapse in France had not been expected. Economists, central banks and international institutions need more accurate tools in order to forecast credit.

First, it is crucial for policymakers to anticipate business cycles, as it conditions the

[1]See figure 1 below.

[2]Klein (2014) show that because of tighter credit conditions, EU countries with high shares of SMEs have experienced, on average, a slower output growth over the 2009-2012 period compared to EU members with lower shares of SMEs. These findings coincide with the conclusions of Kannan (2010) for OECD countries and of Kashyap, Lemont & Stein (1994) for the US. As a whole, Gilchrist & Mojon (2014) confirm that credit shocks may lead to sizable contraction in output, increase in unemployment and decline in inflation.

[3]Note that a strand of this literature, mainly focusing on the Italian case, also analyses the impact of the sovereign debt crisis on credit conditions. See for instance Zoli (2013).

right timing for their policies. In this respect, a relevant model for credit would improve investment and consumption forecasts. Even more, it would allow anticipating the severity of a forthcoming recession. Indeed, according to a comprehensive study by Jordà, Schularick & Taylor (2011*a*), based on more than 200 recession episodes in 14 advanced countries between 1870 and 2008, credit-intensive expansions tend to be followed by deeper recessions and slower recoveries. Cross-sectional analysis focusing on the Great Recession confirmed that the pre-crisis level of credit or credit growth are significant factors for explaining the crisis severity[4]. Second, a better understanding of credit would allow assessing the potential occurrence of credit crunch and credit rationing. This would imply a model that is different from those prevailing in 'normal time'. Therefore, it is worth examining whether some specific indicators (e.g. balance-sheet ratios, spreads, equity prices, ...) could announce episodes of credit collapse. They could act as leading signals for policymakers, indicating regime switching in credit dynamics, or more directly credit crunch.

Next, understanding and anticipating credit dynamics is important for gauging overall financial risk, and the risk of financial crisis in particular. Numerous studies have already highlighted the link between development in credit markets and financial turmoils[5]. This is precisely one reason why Basel III suggests to adjust the capital buffer range above the minimum level normally required '*when there are signs that credit has grown to excessive levels*' (BCBS (2010, p.7)). For the same reason, a part of the current abundant research on systemic risk indicators focuses on credit distribution[6]. Therefore, long-lasting deviations of bank loans from their 'normal' path represent an alert, that may be cross-checked with other warning indicators.

Finally, beyond these structural motives, research on credit can be justified by the

[4] See Lane & Milesi-Ferretti (2011), Cecchetti, King & Yetman (2011), Jordà, Schularick & Taylor (2011*b*), Feldkircher (2014).

[5] Typically, scrutinizing 14 countries over the years 1870-2008, Schularick & Taylor (2012) find that credit growth is a powerful predictor of financial crisis. See also Dermigüç-Kunt & Detragiache (1998), Kaminsky & Reinhart (2000), Borio & Lowe (2002), Borio (2014) and Bezemer & Grydaki (2014).

[6] See for instance Babecky, Havranek, Mateju, Rusnak, Smidkova & Vasicek (2012).

current unprecedented political context. Banks have to cope with a new regulatory environment. Studying the impact of stronger bank capital and liquidity requirements on the cost and volume of credit is important to assess the regulation costs and benefits. Moreover, central banks are conducting unconventional monetary policies, whose objectives are to foster recovery by stimulating credit (Darracq-Paries & Santis (2013)). It thus becomes crucial for central bankers to have tools for evaluating the right dosage of such policies. These points require reliable models for explaining and forecasting credit.

However, the vast majority of the aforementioned papers mainly focus on bank lending rates and interest rate spreads. Attempts to model credit dynamics *per se* are very scarce. The most advanced proposals come from Sorensen, Marquès-Ibanez & Rossi (2009) and Calza, Manrique & Sousa (2006) for the euro area, Casolaro, Eramo & Gambacorta (2006) for Italy, and Hülsewig (2003) for Germany. They all rely on Vector Error-Correction Models (VECM). The recent financial, banking and sovereign debt crises require an update of empirical methods and of the key determinants to consider for explaining and forecasting credit. This is precisely the objective of this paper. We seek to develop a parsimonious model for explaining and forecasting credit, while gauging the marginal informational content of some simple leading indicators. Additionally, we investigate non-linearity in credit dynamics. Our contribution is original too in that it is applied to the French context, which has been ignored so far in the literature, and deals with a period combining both good times and crisis. However, it is worth highlighting that the models, the methods and the variables suggested in this paper could be applied to any country.

The rest of the paper is organized as follows. Section 2 is devoted to the development of a parsimonious Vector Auto-Regressive (VAR) model, which constitutes an immediate and intuitive way of modelling dynamic linkages between key variables in explaining the credit dynamics. Section 3 intends to propose an alternative model, namely a Vector Error Correction Model (VECM), in line with the existing literature on aforementioned European countries. The relative forecast accuracy of these two rival models is compared in section 4. Section 5 exploits the marginal predictive content of a broad set of exogenous indicators. Section 6 evaluates the advantages and the drawbacks in considering the potential non-linearity in credit dynamics. Section 7 concludes and suggests some extensions.

2 A parsimonious credit model

An immediate and intuitive way of modeling dynamic linkages between economic variables consists of developing a VAR model, defined as follows:

$$X_t = \sum_{i=1}^{p} \Psi_i W_{t-i} + \Theta D_t + E_t \tag{1}$$

with X the vector of three endogenous variables: the flow of bank loans to non-financial firms as a share of GDP (noted $LOAN$), the investment rate (noted INV), and the real bank lending rate (noted BLR). These variables are supposed to be highly interconnected and to characterize the main conditions on the credit market. W additionally includes two exogenous variables: the real 3-Month Euribor rate (noted $EURIBOR$), and the real interest rate on bonds issued by non-financial corporations (noted $BOND$). The latter allows considering the substitution between banking and market debts. Rendering these interest rates endogenous would be too costly in terms of degrees of freedom, and would also imply considerations that are not crucial regarding the scope of this paper. Finally, D_t is a vector of deterministic variables, and $E = (e_{LOAN}, e_{BLR}, e_{INV})'$ is the vector of the residuals.

Credit data comes from the Monetary and Financial Institutions (MFI) balance sheet statistics collected by the Banque de France. Whether considering flows or stock of outstanding credit is a debatable issue. We consider flows to be a more relevant metric for our purpose. First, in the existing literature, loans are usually supposed to depend on an other flow variable, namely investment, in credit demand functions (see Friedman & Kuttner (1993, p.213) for instance). In turn, current investment may be disconnected from loans granted some time ago, although included in the outstanding amount of loans. Furthermore, the purpose of our model is to explain and anticipate ongoing and future credit; past credit feeding into outstanding loans is not important in this respect. It could even be misleading, if for instance a rapid credit growth in the past compensates for a current decline. Data on GDP and investment of non-financial corporations come from the INSEE (the French National Institute of Statistics and Economic Studies) database. The retail lending rate (BLR) deals with all the maturities and volumes. It comes from the ECB statistics, like the 3-month Euribor rate ($EURIBOR$). Last, the average interest rate on debt securities ($BOND$) is computed by the Banque de France. These three interest rates are expressed in real terms, using the HCPI inflation rate as a deflator. All data series but the interest rates are seasonally adjusted. They are represented in the figure 1. Descriptive statistics are reported in table 6 in appendix.

According to the ADF tests reported in table 7 in appendix, all the variables are $I(1)$. However, following Sims, Stock & Watson (1990), a VAR in levels with $I(1)$ variables can implicitly take the cointegrated relationships into account. In such a case, the estimated coefficients are consistent, and the asymptotic distribution of the estimated parameters remains standard.

The table 8 in appendix reports the results of this VAR model estimation. The latter is based on quarterly data over the 1994Q1 - 2013Q3 period, therefore spanning at least one entire business cycle and covering good times and situations of financial stress as well. The order p is equal to 2, as suggested both by the Akaike and Schwarz criteria. As shown in the lower part of the table 8, the tests of no autocorrelation and the tests of non stationarity reveal that the residuals of the VAR are stationary white noises. This means that implicit

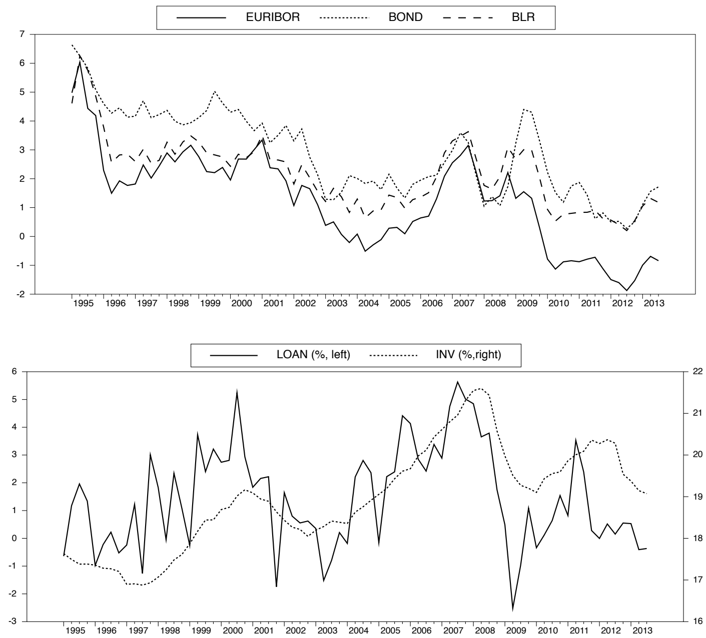

Figure 1: VECM and VAR model data (in level)

cointegrated relations have actually been taken into account.

The main impulse response functions (IRF) of the VAR, based on a standard Cholesky decomposition, are represented in figure 6 in appendix. First, an unexpected 50 bp increase in BLR leads to a significant decrease of the loan to GDP ratio during six quarters. The maximum effect is reached three quarters after the initial shock, with a fall of $LOAN$ by 0.60 percentage point. The corresponding cumulated reduction reaches -1.77%. Most of the estimations concerning the impact of the Basel III regulation on the BLR consider an increase by 0.40 to 0.60 pb at most[7]. According to our IRFs, such an evolution would have limited impact on loans in the short-run. Second, the lower left hand-side plot shows that a one percentage point rise of the loan to GDP ratio triggers an immediate and surprising two quarters drop of the BLR. One explanation can rely on the fact that, for a given nominal bank rate, the increase in loans during an economic boom can coincide with higher inflation

[7]See for instance King (2010) and Elliott, Salloy & Oliveira Santos (2012).

and thus a lower real BLR. Nonetheless, the response of the BLR becomes positive from the third to the ninth quarter following the initial shock, such that the cumulated impact (form the 1st to the 9th quarter) is positive. Next, the upper right-hand side plot indicates that a 0.5 percentage point increase in the investment rate significantly stimulates loans, with a peak of +2% one quarter after the shock. The cumulated impact reaches +4.3%. In turn, investment is significantly sensitive to loan innovations. As indicated by the lower right-hand side plot, a one-percentage point increase in loans has a two-year positive effect on the investment rate. The cumulated response is somewhat higher than two percentage points. Thus the VAR model is not only econometrically, but economically valid as well. It is rational to use it for forecasting purposes.

The figure 2 reproduces the one to four quarters ahead dynamic[8] forecasts for $LOAN$, stemming from the VAR model (in dashed line). As usual, the forecasting errors increase with the horizon. Yet for h higher than two quarters, the predictive power of the model deteriorates, so much so that it appears unrealistic to search for more than 1-year ahead accurate loan forecasts. However, despite the exceptional large swings of loan flows observed from 2007 to 2012, the VAR model manages to offer reliable 1 and 2-quarter ahead predictions. Moreover, according to table 9 in appendix, hypothesis of no bias of the forecast errors, no serial correlation, and efficiency, are not rejected at usual risk levels. So, the VAR model is relevant for forecasting credit.

Nevertheless, as it is common in the literature, it is worth checking whether these forecasts are significantly more accurate than those obtained with alternative models. To this perspective, the next section is devoted to the development of a Vector Error Correction Model (VECM). As previously mentioned, this natural rival model has been used for some other European countries. The main difference with the VAR model is that the VECM

[8]The forecasts are 'dynamic' in that forecasts computed at earlier horizons are used for the lagged dependent variable terms while forecasting for later horizons. For instance, the forecasts for time $t+1$ will be used as the first–period lag value for computing the forecasts at time $t+2$, and so on.

explicitly takes the cointegrating relationships into account.

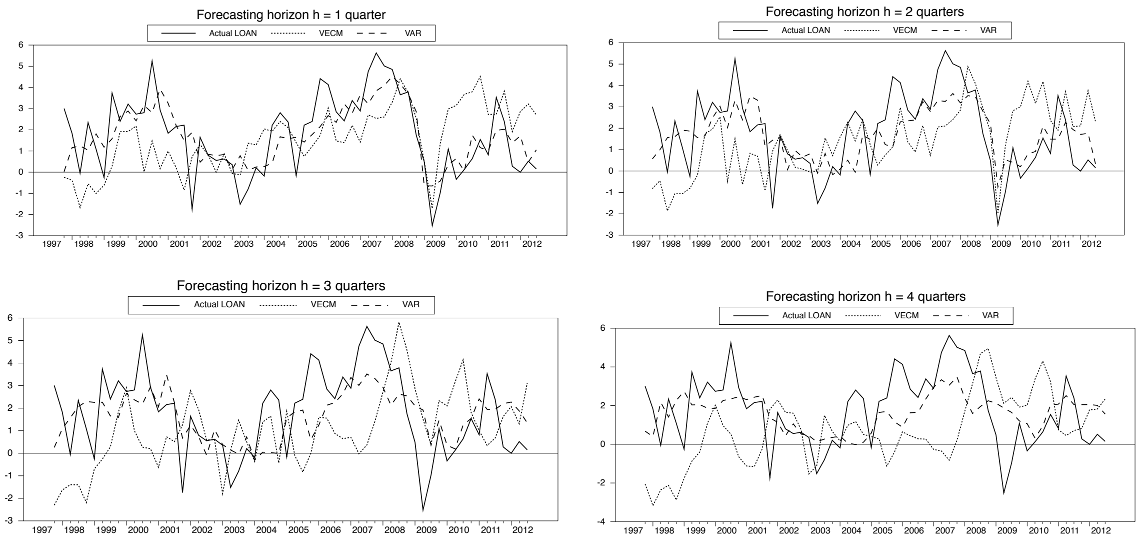

Figure 2: LOAN forecasts (credit flow on GDP) - VECM and VAR models

3 A VECM as an alternative model

Using the same notations as before, the VECM is defined such as $\Delta X_t = \Pi W_{t-1} + \sum_{i=1}^{p'} \Phi_i \Delta W_{t-i} + \Gamma_D D_t + \epsilon_t$. Δ is the difference operator. $\epsilon_{j,t}$ is a vector of white noise residuals. As usual, we can write $\Pi \equiv \rho\alpha'$, where the columns of the matrix α contain the cointegrating vectors, and the columns of the matrix ρ contain the loading factors. Two long-run relationships are sought in particular. The first one is a long-run credit demand equation, such as:

$$LOAN_t = \alpha_{1,0} + \alpha_{1,1} INV_t + \alpha_{1,2} BLR_t + \alpha_{1,3} BOND_t \tag{2}$$

This equation assumes that the demand for loans is governed by the level of investment, by the cost of credit, and by the cost of private debt securities, a substitute to bank loans. The potential substitution between bank loans and debt securities, depending on the spread between BLR and $BOND$, is thus modelled. The expected signs are $\alpha_{1,1} > 0$, $\alpha_{1,2} < 0$ and $\alpha_{1,3} > 0$.

The other expected long run equation is an inverted supply function of bank loans given by:

$$BLR_t = EURIBOR_t + \alpha_{2,0} \tag{3}$$

According to this equation, the bank lending rate in the long run is given by the short term interest rate plus a positive constant term $\alpha_{2,0}$. It is common in the literature on the financial accelerator to consider the latter as an external financial premium, depending on the characteristics of the borrower. This relation matches the credit supply function of Oliner & Rudebusch (1996) and Bernanke, Gertler & Gilchrist (1999) for instance. According to the bank capital channel, the external financial premium should also be related to the balance sheet structure of banks (Levieuge (2009), Meh & Moran (2010)). The lower their capital, the higher their external financing cost, which banks ultimately pass on to the firms' credit standards. Gambacorta & Mistrulli (2014) have recently confirmed that firms borrowing from banks endowed by large capital buffers had been less affected by the financial crisis.

In sum, the $LOAN$ equation of the VECM is given by:

$$\begin{aligned} \Delta LOAN_t &= \theta_{1,0} + \rho_{1,1} LRR1_{t-1} + \rho_{1,2} LRR2_{t-1} + \sum_{i=1}^{p'} \beta_{1,i} \Delta LOAN_{t-i} \\ &\quad + \sum_{i=1}^{p'} \gamma_{1,i} \Delta INV_{t-i} + \sum_{i=1}^{p'} \delta_{1,i} \Delta BLR_{t-i} + \sum_{i=0}^{p'} \omega_{1,i} \Delta BOND_{t-i} \\ &\quad + \sum_{i=0}^{p'} \phi_{1,i} \Delta EURIBOR_{t-i} + \varepsilon_{1,t} \end{aligned} \tag{4}$$

with $LRR1$ and $LRR2$ referring to the long-run relationships (2) and (3), respectively[9].

The VECM is estimated over the 1994Q1 - 2013Q3 period. The order p' is set to 3 according to the Akaike criterion. The results of the Johansen's trace test are reported in table 10 in appendix. Two cointegrating vectors are found, at the 5% level (including with the Bartlett correction for small sample). The free estimation of α suggests that these two cointegrating vectors could match *LRR1* and *LRR2*. However, such an identification requires several constraints, as the long run cointegrating relations of the VECM spontaneously depend on all the variables W of the model, such that:

$$LOAN_t = \alpha_{1,0} + \alpha_{1,1} INV_t + \alpha_{1,2} BLR_t + \alpha_{1,3} BOND_t + \alpha_{1,4} EURIBOR_t \quad (5)$$

$$BLR_t = \alpha_{2,0} + \alpha_{2,1} INV_t + \alpha_{2,2} BLR_t + \alpha_{2,3} BOND_t + \alpha_{2,4} EURIBOR_t \quad (6)$$

First, the constraints required for (5) and (6) to match equations (2) and (3), respectively, imply the nullity of several coefficients ($\alpha_{1,4} = \alpha_{2,1} = \alpha_{2,2} = \alpha_{2,3} = 0$). Furthermore, the long-run value of the premium in equation (3), namely $\alpha_{2,0}$, is set to 0.80. This corresponds to the mean value of the BLR-Euribor spread over the sample period. Last, the long-run elasticity of loans to investment ($\alpha_{2,4}$) is assumed to be equal to one[10].

According to the results that are reported in table 1, the constraints are simultaneously not rejected at the usual risk levels. Moreover, all the unconstraint coefficients have the expected sign. So, in terms of identification of the long-run relationships, the VECM previously developed in the literature for Germany, Italy and the euro area seems to be

[9] More precisely, $LRR1_t = LOAN_t - \alpha_{1,0} - \alpha_{1,1} INV_t - \alpha_{1,2} BLR_t - \alpha_{1,3} BOND_t$ and $LRR2_t = BLR_t - EURIBOR_t - \alpha_{2,0}$.

[10] It is frequent in the literature to find a coefficient higher than one. This is usually attributed to missing variables, but no evidence have been provided to date. We have a credible explanation. Indeed, data from the quarterly flow of funds accounts indicate that non-financial corporations' total debt usually exceeds their net borrowing. As it can be seen in an additional appendix, available upon request, this was clearly the case in 2002 and over the 2006-2008 period. The gap can be filled by the financing of foreign direct investment (FDI). Thus FDI might be considered as a determinant of bank loans. However, the time dimension of available FDI data is too short for running reliable VAR or VECM estimations. This point is to be considered a an extension.

relevant for France as well.

	LRR1 (LOAN)		*LRR2* (BLR)	
	Coeff.	T-stat	Coeff.	T-stat
INV	1.000	-	-	-
BLR	-0.273	(-1.316)	-	-
BOND	0.291	(1.632)	-	-
EURIBOR	-	-	1.000	-
CONSTANT	-0.210	(-18.50)	0.800	-
$H0$: The constraints are not rejected:				
$\chi^2(5) = 9.17$ with P-Value = 0.088				

Table 1: Estimated coefficients of the long-run equations

The remaining estimated coefficients are reported in table 11 in appendix. The loan variations significantly and negatively react to the two cointegrating relations; *ceteris paribus*, $\Delta LOAN$ tends to be negative when $LOAN$ is higher than its long-run target, defined by the right-hand side terms of the equation (2). In the same way, a BLR higher than its long-run target pushes credit down. The sensitivity of the variations of the BLR to the two cointegrating relations is less clear. Finally, the long run equations are not significant in the investment equation. The weak exogeneity tests (see table 11) confirm at the 1% risk level that ΔINV and ΔBLR are weakly exogenous. Thus they define with $BOND$ and $EURIBOR$ the long-run target for the endogenous variable $\Delta LOAN$. Note that the coefficients of determination are highly satisfactory (close to 67% for the $\Delta LOAN$ equation). The hypothesis of normality, no conditional heteroskedasticity, and no serial autocorrelation of the residuals are not rejected (at the 1% risk level).

Finally, the examination of the IRFs confirms the dynamic consistency of the VECM[11]. Thus, this model gives a good fitting of actual bank loans, while ensuring consistent theoretical background.

[11] IRFs from the VECM are available upon request.

4 Comparing the two models

There is a conventional wisdom according to which, if the variables are cointegrated, imposing their long-run relationships can produce substantial improvements in forecasts over long horizons. In this line, Engle & Yoo (1987) find that an unrestricted VAR model does better than an error-correction model for short-run forecast horizons. Fanchon & Wendel (1992) also conclude to the superiority of VAR models. However Christoffersen & Diebold (1998) find that explicit cointegration relationships do not necessarily improve long-horizon forecasts. Surprisingly, they would be instead helpful for short-horizon forecasting. All in all, the improvement in forecasting power while imposing cointegration restrictions depends on the strength of the cointegration relationships (Duy & Thoma (1998)). So, whether a VAR model (in levels) is better or not than a VECM is not a foregone conclusion and should be checked on a case-by-case basis.

The dynamic LOAN forecasts obtained with the VECM are reproduced in the figure 2 (see dotted lines), with those stemming from the VAR model (dashed lines). It clearly appears that the VAR yields more accurate loan forecasts than the VECM. The latter sometimes yields misleading forecasts, as for instance in 2000 Q4, 2001 Q4, 2003 Q2, at the beginning of the financial crisis and in 2009 Q2. These observations are verified in the table 2, where the mean squared errors (MSE hereafter) and the results of the usual Diebold-Mariano test (DM test hereafter) are reported. The null hypothesis of equivalent accuracy is always rejected in favor of the VAR model, whatever the forecast horizon and whatever the period.

Thus, the loan forecasts from a VECM - such as those usually used in this literature - are significantly less accurate than those stemming from a simple VAR model in levels. Nonetheless, the figure 2 also indicates that the performances of the (deliberately parsimonious) VAR could be improved. For example, some exogenous indicators related to

Horizon	Period	MSE ratio	DM stat	P-Value
$h = 1$	1997-2013	2.556	4.858	0.000
	2003-2013	2.932	3.989	0.000
	2006-2013	4.187	4.306	0.000
$h = 2$	1997-2013	2.441	3.706	0.000
	2003-2013	2.246	2.432	0.007
	2006-2013	3.221	2.839	0.002
$h = 3$	1997-2013	2.588	4.024	0.000
	2003-2013	2.236	2.578	0.005
	2006-2013	2.614	2.486	0.006
$h = 4$	1997-2013	3.087	3.566	0.000
	2003-2013	2.609	2.393	0.008
	2006-2013	2.987	2.554	0.005

Note: MSE Ratio = MSE(VECM)/MSE(VAR).
DM test is for H0: MSE(VECM) = MSE(VAR).
DM statistics are corrected for $h-1$ serial correlation.

Table 2: DM tests for loan forecasting accuracy: VECM *vs* VAR model

the financial, banking and/or sovereign debt crisis maybe can help to enhance its forecast accuracy. The next section precisely examines this point.

5 Exploiting the marginal predictive content of exogenous indicators

5.1 A broad set of candidates

The exercice consists now of including additional simple indicators in the LOAN equation of the VAR model, to improve its forecast accuracy, and especially to better announce the credit collapse episodes. We will focus on more than 40 variables which are likely to meet this double challenge. They are listed in table 12 with descriptive statistics and source. They can be gathered into 8 categories.

First, we consider indicators from the *Bank Lending Survey*, which is a survey intended for senior loan officers of a representative sample of national banks. It addresses issues such as credit terms and conditions applied to enterprises, as well as assessment on credit demand. This database receives great attention nowadays for analysis and forecasting purposes[12]. We will focus on the well-known BLS indicator of credit standards and especially on its presumed determinants. The latter are: an indicator of banks' access to financial market, an indicator of liquidity need, and two indicators related to the way bankers perceive the economic activity (global and corporate). The predictive content of five additional indicators, supposed to be sub-components of credit standards, will also be investigated; this concerns BLS indicators of banks' margins (on average and on risky loans), indicators of collateral requirements, of credit volume and of loan duration. Last, the BLS indicator of loan demand is also retained as a potential leading variable.

Second, given the post-2008 context, the informational content of three interest rates - not included in the baseline model - is worth being investigated: the interest rate on BBB-rated corporate bonds, the interest rate on the 10-year OAT bond, and the interest rate on covered bonds.

Third, we consider two consolidated banking data, which are important regarding to the bank capital channel: the capital-to-asset and liquidity-to-asset ratios.

Fourth, risk perception is likely to explain credit. Risk indicators may then refine LOAN forecasts. The candidates on this point are: the default probability for non-financial corporations, the *Expected Default Frequency* for firms and for banks, and the CDS premium for banks. They all proved to be important to gauge the tensions on the financing terms during the crisis. Asset Swap Spreads for all rated and for only BBB-rated european non-financial firms are also considered. They constitute an alternative credit risk measure which can lead the information stemming from the CDS market (Mayordomo, Peña & Romo (2011)). Moreover, we will be interested by two spreads that are viewed as proxies of the risk pre-

[12]The BLS indicators are often used as proxy for unobservable variables or for their hypothetical predictive content. See for instance Del Giovane, Eramo & Nobili (2011), de Bondt, Maddaloni, Peydró & Scopel (2010), Hempell & Sorensen (2010), Ciccarelli, Maddaloni & Peydró (2010), Basset, Chosak, Driscoll & Zakrajsek (2014). For a comprehensive analysis of the informational content of the BLS indicators in France, see Levieuge (2014).

mium: the interest rate on covered bonds minus the 10-year OAT interest rate ('spread covered') and the difference between the BBB corporate and the 10-year OAT interest rates ('BBB spread'). Finally, we will focus on two measures of systemic risk: the *SRisk* indicator provided by Brownlees & Engle (2012), which combines both market and balance sheet information[13], and the Composite Indicator of Systemic Stress (CISS), computed by the ECB.

Fifth, credit must be impacted by monetary policy. Beyond EURIBOR, we will consider measures of unconventional monetary policies, whose objectives are in a large part to stimulate credit. In line with the ECB statements and the existing literature on this topic, two unconventional instruments are considered: the amount of long-term refinancing operations (LTRO) and the size of the ECB's balance sheet[14]. Both are expressed as a percentage of the Euro Area GDP. In addition, the potential informational content of the quarterly growth rate of the long-term refinancing operations, and of the ECB balance sheet size, will be analyzed.

Sixth, as usual in this literature (Stock & Watson (2003)), we will take an interest on the marginal predictive content of the following asset prices: the quarterly growth rate of housing prices, the quarterly growth rate of the French equity index CAC40, and the term spread (10-year OAT minus 3-month Euribor rates).

Seventh, we will evaluate the impact of uncertainty. Valencia (2013) demonstrates that uncertainty is an important determinant of credit activity. Ferrara, Marsilli & Ortega (2014) also find that the volatility of stock prices helps to anticipate the output growth. The recent period was precisely characterized by high uncertainty, as suggested by the debates on the hypothetical U, V or W-shaped expected recovery. Uncertainty is here captured by the standard error of the CAC40 index and by the VCAC indicator, a transposition of the

[13] See details at http://vlab.stern.nyu.edu/.

[14] Securities Market Program and the two Covered Bond Purchase Programs are ignored because they were not effective before 2009.

well-known VIX index to the French stock price index.

Last, various original indicators that may be informative under credit rationing are considered. On the one hand, a 'MIX' variable is computed, in line with Kashyap, Stein & Wilcox (1993). This variable is defined as the ratio of bank loans on total short-term external finance. A decrease in this ratio is supposed to signal credit rationing[15]. While the denominator of the original MIX is only made of bank loans and commercial paper, we think that commercial credit is worth being considered too, as it becomes ineluctable in case of cut in the two other ways of financing[16]. The MIX is thus exactly defined as bank loans / (bank loans + commercial paper + commercial credit). The figure 7 in appendix indicates that bank credit decreased more dramatically than its substitutes from 2008 to 2013.

On the other hand, on can imagine that a constrained entrepreneur, if any, moves heaven and earth to find cash, and notably searches for a solution in the Internet. The occurrences of several French keywords like '*crédit trésorerie*' (corresponding to 'cash credit'), '*financement court terme*' ('short financing'), '*crédit court terme*' ('short run credit'), '*délais paiement*' ('extended payment terms'), and '*crédit PME*' ('loans for SMEs') may be real-time indicators of search for financing. Such occurrences are delivered by Google Trends[17]. The five series corresponding to the aforementioned expressions are labeled *Google T1* to *Google T5*, respectively. According to the figure 7, they all indicate that researches about short term financing on Google was intensive in 2008. In line with the credit collapse

[15] From this point of view, Becker & Ivashina (2014) recently used firm-level data to compute such an indicator. They find in particular strong evidence of substitution from loans to bonds when credit standards are tight.

[16] According to the Banque de France, the late payment reached 13 and 9 billions of euros for the SMEs and the intermediate size companies, respectively, at the end of 2011. In 2012 and 2013, only one third of the firms had timely paid their suppliers.

[17] Google Trends does not deliver the absolute number of researches for a given expression, but a relative index scaled between 0 (no research registered) and 100 (maximum audience). Data are available on a monthly frequency. Transformation to quarterly frequency is made the basis of the maximum value of any Google Trends variable over the three months constituting the quarter. Transformation based on the mean values gave similar results in terms of incremental forecasting power.

observed in figure 1 and the evolution of the MIX variable, this observation tends to validate the hypothesis according which the Google trends are fair indicators of liquidity need. Finally, they all suggest that credit has still been a concern since 2009.

5.2 Assessing the incremental predictive content of these exogenous indicators

These additional indicators, noted Z, successively enter the LOAN equation of the VAR. As most of them are not available before the early 2000, the LOAN equation can not be re-estimated on the basis of their respective starting date. So, the coefficients for Z are obtained by regressing the residuals e_{LOAN} of (1) on the past values of Z, such that: $e_{LOAN,t} = \sum_{i=1}^{4} \eta_i Z_{t-i}$. Then, the VAR system with the augmented LOAN equation (where Z_{t-i} are weighted according to η_i) is used to generate LOAN forecasts. Z is a significant leading indicator if it significantly reduces the MSE of the LOAN forecasts compared with the MSE obtained from the baseline VAR model.

BLS Indicator (Z)	R^2	MSE(VAR) / MSE(VAR+Z)			
		$h=1$	$h=2$	$h=3$	$h=4$
BLS Credit Standards (All firms)	13.9	1.203**	1.033	1.092	1.027
BLS Banks' acces to financial markets	0.25	1.054	1.075	1.107	1.130
BLS Banks' liquidity need	2.00	0.167	0.226	0.208	0.145
BLS Economic activity	3.20	1.079	0.950	0.957	0.957
BLS Corporate Business	2.40	1.070	1.117	1.033	0.980
BLS Banks' Margins	4.51	1.094	1.133	1.070	1.047
BLS Banks' Margins on risky loans	11.4	1.179*	1.043	0.994	0.901
BLS Loan Volume	16.2	1.247**	1.224*	1.210*	1.139
BLS Collateral Requirements	10.5	1.168*	1.049	1.102	1.161*
BLS Loan Duration	13.6	1.209*	1.353**	1.341**	1.439***
BLS Demand for loans	3.65	1.084	1.131	1.108	1.090

Note: R^2 refers to the regression of the residuals of the LOAN equation on $Z_{t-1}, \ldots, Z_{t-4}$.
The other figures refer to the ratio of the MSE of the baseline VAR model forecasts, on the MSE of the augmented VAR model forecasts. *,**,*** means that this ratio is significantly different from one, at 10, 5 and 5% level, respectively. The forecasts span the period 2004 Q1 - 2013 Q3. $h = 1$ to 4 is the forecasting horizon.

Table 3: Testing the marginal predictive content of the main BLS indicators

Table 3 reports the results that we obtain with the Bank Lending Survey indicators. Some of them significantly improve the forecasts, but only for one or two horizons. This is the case for the BLS credit standards, for the indicator of banks' margins on risky loans and for the indicator of collateral requirements. Finally, in line with Levieuge (2014), the BLS loan duration indicator is the only one to improve the forecast accuracy for $h = 1$ to $h = 4$.

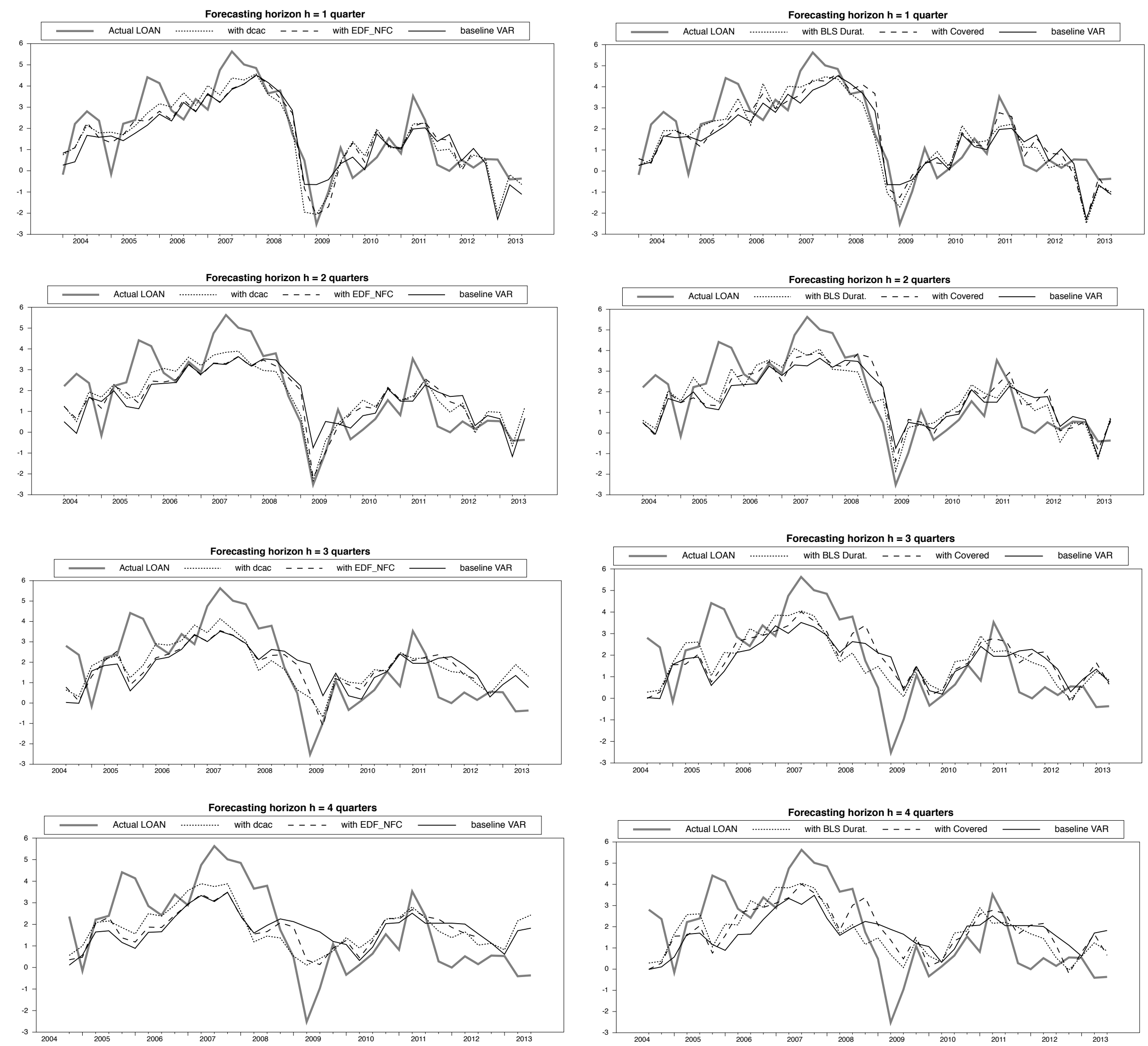

Figure 3: LOAN Forecasts with augmented VAR

Indicator (Z)	R^2	MSE(VAR) / MSE(VAR+Z)			
		$h=1$	$h=2$	$h=3$	$h=4$
BBB interest rate	1.61	1.002	1.028	1.032	1.048
10-year OAT interest rate	5.85	1.095	1.107	1.119	1.109
Interest rate on covered bonds	8.48	1.133*	1.161**	1.148***	1.158***
Capital-to-asset ratio	1.59	1.049	1.077	1.055	1.068
Liquidity-to-asset ratio	7.59	1.116	1.146**	1.094	1.067
Default probability of NFC ($\star$)	9.68	1.086	1.034	1.027	1.026
Expected Default Frequency of NFC	13.4	1.113	1.298**	1.256**	1.247**
Expected Default Frequency of Banks	16.7	1.264*	1.048	1.030	1.039
CDS Premium (Index for France, ($\star\star$))	2.98	1.068	0.943	0.938	0.972
Asset Swap Spread (All, non-financial)	3.34	1.075	1.074	1.080	1.092
Asset Swap Spread (BBB non-financial)	2.60	1.068	1.089	1.079	1.086
Spread Covered (Covered - OAT10)	7.50	1.119	1.149	1.200*	1.230*
BBB Spread (BBB - OAT10)	5.49	1.015	1.028	1.051	1.080
SRISK (Index for France)	2.39	1.016	1.032	1.034	1.028
Composite Indicator of Systemic Stress	4.48	1.069	1.042	1.015	1.001
LTRO	10.3	1.164**	0.985	0.945	0.940
SIZE	9.02	1.154**	1.069	1.024	1.006
LTRO quarterly growth rate	6.32	1.109	0.974	0.984	0.997
SIZE quarterly growth rate	7.69	1.078	1.032	1.026	1.000
Housing price quarterly growth rate	4.72	1.107	1.196	1.148	1.166
CAC40 quarterly growth rate	22.5	1.266*	1.529**	1.393**	1.419**
Term Spread (10-year minus 3-Month)	3.11	1.077	1.059	1.110	1.131
Std. error of CAC40	6.26	1.028	1.107	1.138	1.109
VCAC	10.25	1.108	1.150*	1.088	1.072
MIX	4.08	1.065	0.935	0.941	0.921
Google T1 ($\star\star$)	0.60	1.037	1.031	1.008	1.025
Google T2 ($\star\star$)	16.2	1.295	0.942	1.012	1.026
Google T3 ($\star\star$)	6.18	1.116	0.988	1.034	1.018
Google T4 ($\star\star$)	10.2	1.182*	0.957	1.108	1.105
Google T5 ($\star\star$)	4.81	1.095	1.029	1.026	1.028

Note: R^2 refers to the regression of the residuals of the LOAN equation of the VAR on $Z_{t-1}, ..., Z_{t-4}$. The other figures refer to the ratio of the MSE of the forecasts based on the initial VAR model on the MSE of the forecasts based on the augmented VAR. *,**,*** means that this ratio is significantly different from one, at 10, 5 and 5% level, respectively. The forecasts span the period 2004 Q1 - 2013 Q3, excepted ($\star$) ending in 2012 Q3, and ($\star\star$) beginning in 2006 Q4. $h = 1$ to 4 is the forecasting horizon.

Table 4: Testing the marginal predictive content of additional single indicators

The marginal predictive content of the other indicators is reported in table 4. Several variables give interesting results, but for only few horizons. This is the case for the Spread Covered, the Google T4 indicator, the LTRO and SIZE variables, and for the bank's liquidity-to-asset ratio.

Only three indicators deliver significant incremental information for $h = 1$ to $h = 4$: the growth rate of the CAC40 index[18], the Expected Default Frequency of firms (which is based on stock market information), and the interest rate on covered bonds[19].

The figure 3 illustrates the benefits associated with these three variables and with the BLS duration indicator. The first column of plots indicates that the growth rate of CAC40 (noted $dCAC$) and the Expected Default Frequency for firms (EDF_NFC), in particular, would have been very valuable for announcing the 2008's credit collapse, at least with 1 to 2 quarters ahead, without deteriorating the forecasting power of the model during non-crisis times.

Note that the growth rate of equity prices has a substantial advantage in that it can be freely and easily computed in real-time. At the opposite, forecasts relying on EDF_NFC, on BLS indicators, or on covered bonds would make the forecaster dependent on external publication and calendar. Moreover, the reasons why the CAC40 is a fair leading indicator can be theoretically explained. Asset prices are basically forward-looking. They are supposed to contain information on ongoing economic environment, and then to affect credit demand. The influence of equity prices on credit is also due to supply-side mechanisms. First, stock prices are supposed to be representative of future cash flow, assimilated to the

[18] In this respect, Krainer (2014) recently found that stock prices Granger cause Euro area bank lending.

[19] As a robustness check, loan forecasts have been made with only the augmented LOAN equation of the VAR, namely considering the true values of INV and BLR, instead of their dynamically simulated values. The exercice is less discriminant as forecasts errors for the endogenous variables of the system do not cumulate. Nonetheless, such an univariate framework allows applying the bootstrapped method suggested by Clark & McCracken (2012, p.55) for testing forecast accuracy in case of nested models. The results are unchanged, in the sense that the indicators improving loan forecasts accuracy in our multivariate framework are also found to significantly improve the quality of forecasts in the univariate framework with simulated probability distributions.

net wealth of firms and considered as a proxy of the balance-sheet quality of borrowers in the abundant literature on the financial accelerator. Second, with the financial deregulation, French banks became more vulnerable to financial cycles. Any financial shock has an impact on the asset side of their balance sheet (i.e. on their securities portfolio and in turn on their retained earnings), as well as on the liability side that is subject to capital requirement. So, equity prices may be a good proxy for the banks' balance sheet quality, which in turn influences credit standards, according to the bank capital channel theory.

The financial accelerator and the bank capital channel describe non-linear channels, according to which negative shocks have higher effects than positive ones, in particular in a deteriorated economic and financial context. This suggests switching regimes in the evolution of credit, depending on a threshold variable. This possibility is investigated in the next section.

6 Investigating nonlinear credit dynamics

6.1 Threshold VAR methodology and estimation

The hypothesis tested in this section is the following: the model governing the evolution of credit is not the same whether the financial context is good or bad. In other words, the influence of the determinants of credit changes with the financial context. In line with the models used so far, this assumption is investigated through a Threshold VAR (TVAR) model, following the methodology suggested by Balke (2000). This model allows to endogenously generate regimes shifts, depending on the value τ of a threshold variable V. The TVAR model is defined as:

$$\widetilde{X}_t = A(L)\widetilde{W}_t + B(L)\widetilde{W}_t \times I\left(V_{t-d} > \tau\right) + U_t \tag{7}$$

with $\widetilde{X}$ representing the vector of the endogenous variables $(LOAN, BLR, INV, dCAC)$. $\widetilde{W}$ additionally includes the two exogenous variables $BOND$ and $EURIBOR$. A and B are lag polynomial matrices and U the disturbances. According to the results of the previous section, and given the availability of the data, the growth rate of the CAC40 ($dCAC$) is considered as the potential threshold variable V. $I\left(V_{t-d} > \tau\right)$ is an indicator function that equals 1 when $V_{t-d} > \tau$, and 0 otherwise, so defining the *upper* and the *lower* regime, respectively[20]. Next, equation (7) considers the possibility for a lagged influence of the transition variable on the credit regime; d is set to one. Finally, to guard against overfitting, the possible threshold values are restricted such that each regime has at least $\phi = 20\%$ of the observations plus the number of parameters.

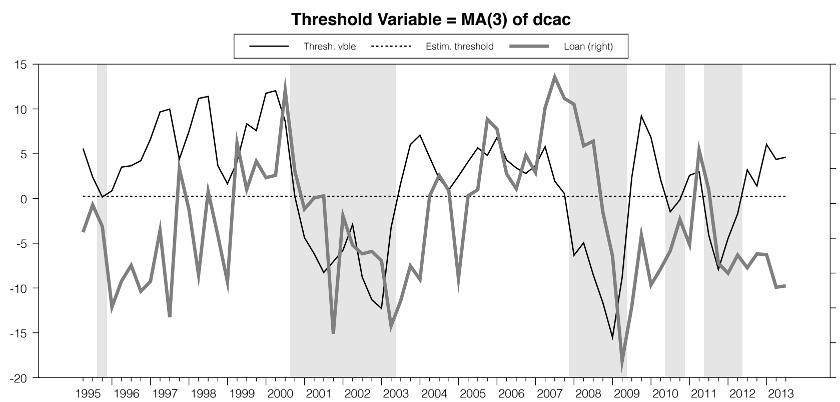

Figure 4: Identification of credit regimes

Interestingly, the estimated threshold value is close to 0 ($\hat{\tau} = 0.235$)[21]. The null hypothesis of no threshold effect is clearly rejected[22], with a statistic of 81.5 and a corresponding P-value equal to 0.00. Inherent regime shifts are represented in figure 4. The shaded areas

[20]As usual, the transition variable is a q-quarter moving average of V, in order to avoid untimely regime switching. See Balke (2000) and Avdjiev & Zeng (2014) for instance. This is all the more justified when V is a volatile variable as equity prices. q is set to 3 in the current investigation.

[21]Due to parsimony concerns, the results of the TVAR estimates are not reported here, but they are available upon request in an additional appendix.

[22]The results are robust to the values of d, q and ϕ. Details are available upon request.

identify the periods of lower regime (i.e. when the threshold variable is below the threshold value $\hat{\tau}$), which concerns in particular the 2000Q4-2003Q2, 2008Q1-2009Q2, end-2010 and 2011Q3-2012Q2 periods. Strikingly, we observe that episodes of major credit decrease occurred under these periods (more obviously after 2000). In other words, the periods of low equity price growth, which include bubble busts, coincide with sharp decreasing credit. This result is consistent with the recent findings of Delis, Kouretas & Tsoumas (2014). They show that banks' lending behavior changes during 'anxious periods', defined and identified as situations in which perceptions and expectations on future conditions are pessimistic. One can reasonably consider that periods of declining asset prices match such 'anxious periods'.

6.2 Forecasting with the TVAR model

The TVAR is now used to generate credit forecasts. The latter will be compared with the output of the baseline VAR model and especially those of the VAR model augmented with $dCAC$. As a first evaluation, we consider that $I(.)$ in equation (7) is perfectly known. This means that the future upper and lower regimes are correctly identified, in perfect compliance with the shaded parts of the figure 4.

TVAR with true regimes				
	MSE(VAR)/MSE(TVAR)			
Alternative Model	h=1	h=2	h=3	h=4
Baseline VAR	1.642**	1.047	1.675**	1.571**
VAR + dCAC	1.297	0.694	1.183	1.087
TVAR with forecasted regimes				
	MSE(VAR)/MSE(TVAR)			
Alternative Model	h=1	h=2	h=3	h=4
Baseline VAR	0.837	0.707	1.130	1.270
VAR + dCAC	0.661	0.468	0.798	0.879
% Regime Errors	10.25	15.38	25.64	33.33

Period 2004 Q1 - 2013 Q3.

Table 5: The marginal predictive content of the TVAR model

The higher panel of the table 5 reports the corresponding MSE ratios. The TVAR is found to be better than the baseline model (excepted for $h = 2$) at the 5% level over the 2004:Q1 - 2013:Q3 period. However, it does not generally appear to perform better than the VAR model augmented with $dCAC$. These results also hold for the whole 1997Q1 - 2013Q3 period. Nevertheless, as shown in figure 5, the TVAR model seems to better predict peaks and troughs than any other model, as for instance in mid-2007 and in 2009Q2, and for longer forecast horizons in particular.

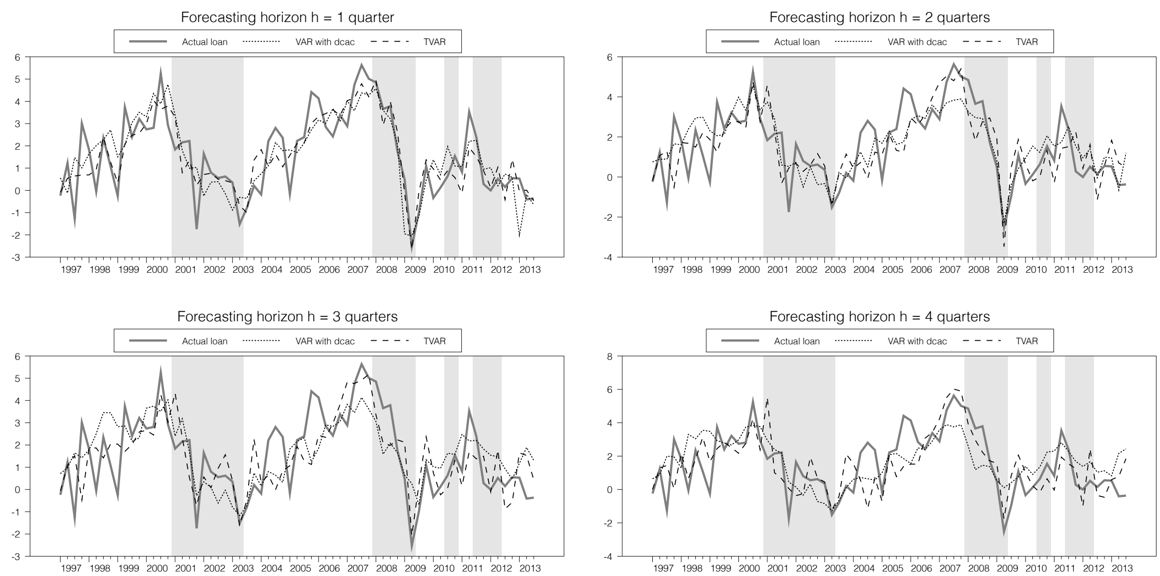

Figure 5: Loan forecasts: TVAR *vs* Augmented VAR

Nonetheless, in practice, the future regimes are unknown and have to be forecasted too. As the threshold variable is also a dependent variable in the model, the TVAR is used to simultaneously generate forecasts of $dCAC$, forecasts of the regime, and ultimately forecasts of loans. The lower part of the table 5 indicates that in this case the TVAR is neither significantly better than the augmented VAR model, nor significantly more accurate than the baseline VAR model.

The figure 8 in appendix, where grey shaded parts correspond to the forecasted lower regime, brings more insight. For $h = 1$, the TVAR clearly fails to announce the 2008-2009 credit collapse episode, contrary to the augmented VAR model. Next, for $h = 2$, some very large forecasting errors are observed, for instance in 1999, 2002 and early 2008. Similarly, forecasts appear to be excessively volatile in 2008-2009 for $h = 3$. Finally, for $h = 4$, the TVAR model announces much more low regimes than what is actually found *ex post*. The mitigated performances of the TVAR rely on its inability to duly predict the regime switchings. The last line of table 5 reports that the TVAR announces the wrong regime (lower instead of upper, and vice versa) in 10% (for $h = 1$) to one third (for $h = 4$) of the cases. This illustrates the potential drawbacks of such a model, which crucially relies on its ability to predict the threshold variable. Otherwise, errors concerning the expected regime exacerbates forecasting errors, to the point that their variance can finally be higher than those obtained with a linear model.

7 Concluding remarks

The aim of this paper was to develop and compare parsimonious models, incorporating possibly leading indicators, to explain and forecast credit to non financial companies. This framework is applied to the French case, during calm periods as well as situations of crisis. To our best knowledge, this is the first attempt to model credit dynamics for France.

The results first indicate that a VAR model with variables in levels generates more accurate credit forecasts than the VECM previously developed for other European countries. Second, beyond the financial, banking and economic variables that have been widely analyzed, surveyed and commented since 2008, we find that very few of them are useful for improving credit forecast accuracy. Among these useful additional exogenous variables, the growth rate of CAC40 appears to be the most interesting leading indicator. This can be theoretically justified. Stock prices represents for future cash flow, a fair proxy of the borrowers' balance-sheet quality according to the literature on the financial accelerator. The lower the equity prices, the higher the external financial premium that firms must bear and hence the lower their borrowing capacity. Moreover, any change in equity prices affects both the liability and the asset side of banks' balance-sheets. According to the bank capital channel theory, any decline in asset prices depreciates the value of banks' securities portfolio and decreases their retained earnings. The resulting fall in their own equity capital leads the banks to tighten credit conditions and/or to diminish credit supply.

These theories describe nonlinear mechanisms. We have therefore considered switching regimes in credit dynamics, depending on the evolution of equity prices. Tests and estimations based on a Threshold VAR (TVAR) model confirm that the growth rate of CAC40 constitutes a significant transition variable for explaining shifts in credit dynamics. However, concerning forecast accuracy, the TVAR model is not significantly better than the VAR model augmented with equity prices. Indeed, the nonlinear model fails to accurately predict the right regime (i.e. to forecast the threshold variable).

Further investigation should look deeper into the non-linear hypothesis. Certainly, the TVAR model used in this paper is initially devoted to explain credit, not equity prices. A possible extension would consist of searching for another - external - model specifically designed for forecasting the switching from a regime to another. Moreover, some single indicators among the ones considered in section 5 could be relevant threshold variables, although they are not significant leading indicators.

Furthermore, we think that it would be interesting to consider foreign direct investment (FDI) as an additional determinant of credit demand. Unfortunately, the short time dimension of available FDI data prevents a VAR model to be fairly estimated. A Bayesian VAR would then be a solution, all the more that such a method allows for the density forecast of any variable to be easily updated as new information becomes available.

Finally, while this paper is devoted to the French case, the methods used can be applied to any country. It would be interesting for example to investigate whether the indicators of credit rationing are more relevant in European periphery countries than they are in France. More generally, among the large set of potential leading and threshold indicators we focus on in this paper, some are likely to be significant in some countries but insignificant in others. This should depend on the way the financial crisis impacted the considered countries. For instance, the 10-year sovereign bond rate had probably been more decisive in some peripheral Eurozone countries than in France or Germany. Differences in results will ultimately depend on structural characteristics, which determine the sensitivity of borrowers and lenders' balance sheet structures to financial and real shocks.

References

Avdjiev, S. & Zeng, Z. (2014), 'Credit growth, monetary policy, and economic activity in a three-regime TVAR model', *BIS Working Papers* (449).

Babecky, J., Havranek, T., Mateju, J., Rusnak, M., Smidkova, K. & Vasicek, B. (2012), 'Banking, debt, and currency crises. Early Warning Indicators for developed countries', *ECB Working Paper* (1485).

Balke, N. (2000), 'Credit and economic activity: credit regimes and nonlinear propagation of shocks', *The Review of Economics and Statistics* **82**(2), 344–349.

Basset, W., Chosak, M., Driscoll, J. & Zakrajsek, E. (2014), 'Changes in bank lending standards and the macroeconomy', *Journal of Monetary Economics* (62), 23–40.

BCBS (2010), *Basel III: A Global Regulatory Framework for More Resilient Banks and Banking Systems*, (Revised June 2011), Basel: Bank for International Settlements.

Becker, B. & Ivashina, V. (2014), 'Cyclicality of credit supply: firm level evidence', *Journal of Monetary Economics* (62), 76–93.

Bernanke, B., Gertler, M. & Gilchrist, S. (1999), The financial accelerator in a quantitative business cycle framework, *in* J. Taylor & M. Woodford, eds, 'Handbook of Macroeconomics', Vol. 1, Amsterdam : North-Holland, chapter 21, pp. 1341–1393.

Bezemer, D. & Grydaki, M. (2014), 'Financial fragility in the great moderation', *Journal of Banking & Finance* **49**, 169–177.

Borio, C. (2014), 'The financial cycle and macroeconomics: What have we learnt?', *Journal of Banking and Finance* **45**, 182–198.

Borio, C. & Lowe, P. (2002), 'Asset prices, financial and monetary stability: Exploring the nexus', *BIS Working Paper* (114).

Brownlees, C. & Engle, R. (2012), 'Volatility, correlation and tails for systemic risk measurement', *available at SSRN: http://ssrn.com/abstract=1611229* .

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

Casolaro, L., Eramo, G. & Gambacorta, L. (2006), 'Un modello econometrico per il credito bancario alle imprese in Italia"', *Moneta e Credito* **59**(234), 151–183.

Cecchetti, S., King, M. & Yetman, J. (2011), 'Weathering the financial crisis: Good policy or good luck?', *BIS Working Papers* (351).

Christoffersen, P. & Diebold, F. (1998), 'Cointegration and long-horizon forecasting', *Journal of Business and Economic Statistics* **16**(4), 450–458.

Ciccarelli, M., Maddaloni, A. & Peydró, J. (2010), 'Trusting the bankers: A new look at the credit channel of monetary policy', *ECB Working Paper Series* (1228).

Clark, T. & McCracken, M. (2012), 'Reality checks and comparisons of nested predictive models', *Journal of Business & Economic Statistics* **30**(1), 53–66.

Darracq-Paries, M. & Santis, R. D. (2013), 'A non-standard monetary policy shock: The ECB's 3-year LTROs and the shift in credit supply', *ECB Working Paper* (1508).

de Bondt, G., Maddaloni, A., Peydró, J. & Scopel, S. (2010), 'The euro area bank lending survey matters: Empirical evidence for credit and output growth', *European Central Bank Working Paper* (1160).

Del Giovane, P., Eramo, G. & Nobili, A. (2011), 'Disentangling demand and supply in credit developments: A survey-based analysis for italy', *Journal of Banking & Finance* **35**(10), 2719– 2732.

Delis, M., Kouretas, G. & Tsoumas, C. (2014), 'Anxious periods and bank lending', *Journal of Banking & Finance* (38), 1–13.

Dermigüç-Kunt, A. & Detragiache, E. (1998), 'The determinants of banking crises in developing and developed countries', *IMF Staff Papers* **45**(1).

Duy, T. & Thoma, M. (1998), 'Modeling and forecasting cointegrated variables: Some practical experience', *Journal of Economics and Business* **50**(3), 291–307.

Elliott, D., Salloy, S. & Oliveira Santos, A. (2012), 'Assessing the cost of financial regulation', *IMF Working Paper* (12/233).

Engle, R. & Yoo, B. (1987), 'Forecasting and testing in co-integrated systems', *Journal of Econometrics* **35**(1), 143–159.

Fanchon, P. & Wendel, J. (1992), 'Estimating var models under non-stationarity and cointegration: Alternative approaches for forecasting cattle prices', *Applied Economics* **24**(2), 107–217.

Feldkircher, M. (2014), 'The determinants of vulnerability to the global financial crisis 2008 to 2009: credit growth and other sources of risk', *Journal of international Money and Finance* (43), 19–49.

Ferrara, L., Marsilli, C. & Ortega, J.-P. (2014), 'Forecasting growth during the Great Recession: Is financial volatility the missing ingredient?', *Economic Modelling* (36), 44–50.

Friedman, B. & Kuttner, K. (1993), 'Economic activity and the short-term credit markets: An analysis of prices and quantities', *Brookings Papers on Economic Activity* **24**(2), 193–283.

Gambacorta, L. & Mistrulli, P. (2014), 'Bank heterogeneity and interest rate setting: What lessons have we learned since lehman brothers?', *Journal of Money, Credit and Banking* **46**(4), 753–778.

Gilchrist, S. & Mojon, B. (2014), 'Credit risk in the euro area', *NBER Working Paper* (20041).

Hempell, H. & Sorensen, C. (2010), 'The impact of supply constraints on bank lending in the euro area: Crisis induced crunching?', *ECB Working Paper* (1262).

Hülsewig, O. (2003), 'Bank behavior, interest rate targeting and monetary policy transmission', *Würzburg Economic Papers* (43).

Jordà, O., Schularick, M. & Taylor, A. (2011*a*), 'When credit bites back: Leverage, business cycles and crises', *NBER Working Paper* (17621).

Jordà, O., Schularick, M. & Taylor, A. M. (2011*b*), 'Financial crises, credit booms, and external imbalances: 140 years of lessons', *IMF Economic Review* **59**(2), 340–378.

Kaminsky, G. & Reinhart, C. (2000), 'On crises, contagion and confusion', *Journal of International Economics* **51**, 145–168.

Kannan, P. (2010), 'Credit conditions and recoveries from recessions associated with financial crises', *IMF Working Paper* (83).

Kashyap, A., Lemont, K. & Stein, J. (1994), 'Credit conditions and the cyclical behaviour of inventories', *Quarterly Journal of Economics* (109), 565–592.

Kashyap, A., Stein, J. & Wilcox, D. (1993), 'Monetary policy and credit conditions: Evidence from the composition of external finance', *American Economic Review* **83**(1), 78–98.

King, M. (2010), 'Mapping capital and liquidity requirements to bank lending spreads', *BIS Working Paper* (324).

Klein, N. (2014), 'Small and medium size enterprises, credit supply shocks, and economic recovery in Europe', *IMF Working Paper* (98).

Krainer, R. E. (2014), 'Monetary policy and bank lending in the euro area: is there a stock market channel or an interest rate channel?', *Journal of International Money and Finance* **49**(B), 283–298.

Lane, P. & Milesi-Ferretti, G. (2011), 'The cross-country incidence of the global crisis', *IMF Economic Review* **59**, 11–110.

Levieuge, G. (2009), 'Bank capital channel and counter-cyclical prudential regulation in a DSGE model', *Louvain Economic Review* **75**(4), 425–460.

Levieuge, G. (2014), 'Cohérence et contenu prédictif des indicateurs du Banque Lending Survey pour la france', *Revue Française d'Economie* **XXIX**(2), 245–247.

Mayordomo, S., Peña, J. & Romo, J. (2011), 'The effect of liquidity on the price discovery process in credit derivative markets in times of financial distress', *The European Journal of Finance* **17**(9-10), 851–881.

Meh, C. & Moran, K. (2010), 'The role of bank capital in the propagation of shocks', *Journal of Economic Dynamics and Control* **34**(3), 555–576.

Oliner, S. & Rudebusch, G. (1996), 'Is there a broad credit channel for monetary policy?', *Economic Review, Federal Reserve Bank of San Francisco* (1), 5–13.

Schularick, M. & Taylor, A. (2012), ‘Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008’, *American Economic Review* **102**(2), 1029–61.

Sims, C., Stock, J. & Watson, M. (1990), ‘Inference in linear time series models with some unit roots’, *Econometrica* **58**, 113–144.

Sorensen, K., Marquès-Ibanez, D. & Rossi, C. (2009), ‘Modelling loans to non-financial corporations in the euro area’, *ECB Working Paper* (989).

Stock, J. & Watson, M. (2003), ‘Forecasting output and inflation: The role of asset prices’, *Journal of Economic Literature* **41**(3), 788–829.

Valencia, F. (2013), ‘Aggregate uncertainty and the supply of credit’, *IMF Working Paper* (241).

Zoli, E. (2013), ‘Italian sovereign spreads: Their determinants and pass-through to bank funding costs and lending conditions’, *IMF Working Paper* (13/84).

Appendix

Series	Mean	Std Err.	Min	Max	Source
Loans (flow on GDP)	1.38	1.79	-2.51	5.62	Banque de France
Investment rate	18.89	1.22	16.87	21.59	INSEE
Inflation rate	1.69	0.73	-0.45	3.61	Banque de France
Real Bank Lending Rate	2.32	1.32	0.20	6.25	Banque de France
Real 3-Month Euribor	1.40	1.74	-1.87	6.03	Banque de France
Real interest rate on bonds	3.02	1.63	0.27	6.66	Banque de France

Note: statistics over the period 1994 Q1 - 2013 Q3.

Table 6: Main variables - descriptive statistics and source

	With constant		With trend	
	lags	T-stat	lags	T-stat
$LOAN$	4	-2.81	4	-2.70
INV	2	-1.72	4	-2.70
BLR	3	-2.67	4	-2.14
$EURIBOR$	2	-1.80	3	-3.06
$BOND$	4	-1.12	4	-2.28
	With constant		**No constant**	
	lags	T-stat	lags	T-stat
$\Delta LOAN$	3	-4.62**	3	-4.66**
ΔINV	4	-3.22*	4	-3.24**
ΔBLR	3	-5.86**	2	-5.46**
$\Delta EURIBOR$	2	-5.35**	2	-5.18**
$\Delta BOND$	3	-7.05**	3	-6.80**
Critical values	At 5% level		At 1% level	
With no constant	-1.94		-2.59	
With constant	-2.90		-3.52	
With trend	-3.47		-4.09	

*,** indicates rejection of $H0$ (unit root) at 5 and 1% level respectively.

Table 7: Augmented Dickey-Fuller tests

VAR Model	*LOAN*		*INV*		*BLR*	
	Coeff.	St. Err.	Coeff.	St. Err.	Coeff.	St. Err.
BLR_{t-1}	-0.527	(0.838)	-0.058	(0.094)	0.139	(0.274)
BLR_{t-2}	-0.574	(0.847)	0.008	(0.095)	0.122	(0.277)
$LOAN_{t-1}$	0.129	(0.147)	0.023	(0.016)	-0.026	(0.048)
$LOAN_{t-2}$	-0.027	(0.144)	0.026	(0.016)	-0.066	(0.047)
INV_{t-1}	4.012	(1.075)	1.426	(0.121)	0.317	(0.352)
INV_{t-2}	-3.012	(0.967)	-0.632	(0.109)	0.010	(0.317)
$EURIBOR_{t-1}$	0.491	(0.779)	0.087	(0.088)	0.623	(0.255)
$EURIBOR_{t-2}$	0.207	(0.761)	-0.066	(0.086)	-0.247	(0.249)
$BOND_{t-1}$	0.264	(0.425)	-0.007	(0.048)	0.247	(0.139)
$BOND_{t-2}$	0.256	(0.418)	0.006	(0.047)	-0.143	(0.137)
TREND	-0.016	(0.033)	0.011	(0.003)	-0.017	(0.011)
Constant	-16.75	(7.727)	3.093	(0.874)	-4.267	(2.533)
R^2	0.514		0.987		0.886	
Ljung-Box Q test for residuals						
	Stat.	P-Value	Stat.	P-Value	Stat.	P-Value
lags = 4	4.080	0.395	6.065	0.194	7.173	0.127
lags = 8	12.99	0.111	9.924	0.270	10.70	0.218
lags = 12	16.68	0.162	14.90	0.246	14.17	0.289
Unit Root tests for residuals (without trend nor constant)						
	Stat. (lags)		Stat. (lags)		Stat. (lags)	
ADF Test	-4.198 (2)		-3.503 (3)		-4.124 (4)	
PP Test	-10.14 (4)		-10.26 (4)		-8.331 (4)	
Critical values at 5% level for ADF and PP tests are -2.597 and -3.523						

Table 8: VAR estimates and tests

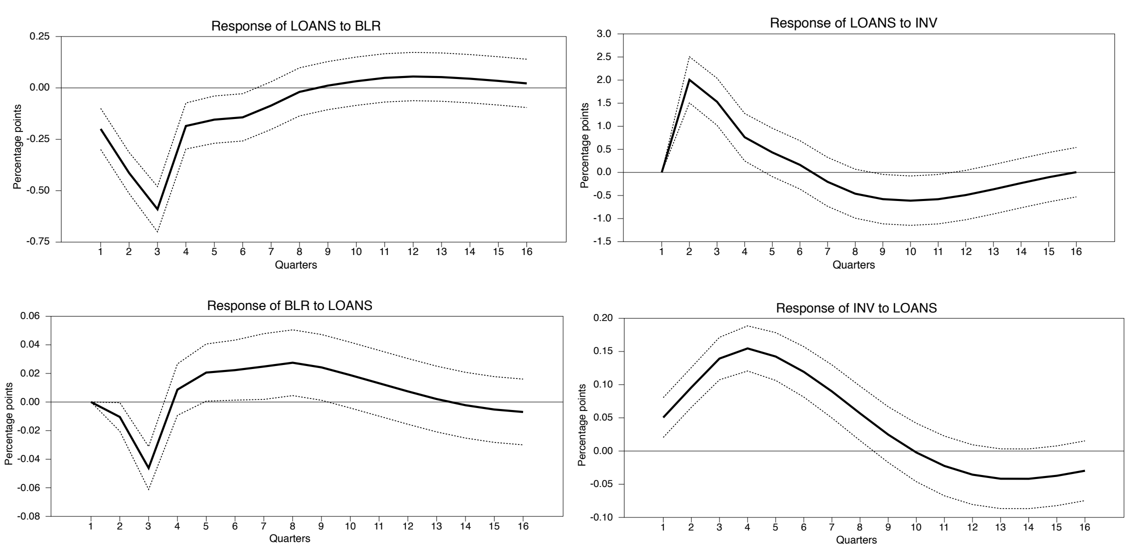

Figure 6: Impulse response functions - VAR Model

Horizon:	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	$h=7$	$h=8$
No bias (a)	0.879	0.689	0.607	0.562	0.439	0.359	0.387	0.298
No serial correlation (b)	0.154	0.145	0.103	0.096	0.089	0.056	0.051	0.039
Efficiency (c)	0.783	0.439	0.732	0.709	0.847	0.945	0.739	0.991

(a) H0: $E_t(error_{t+h}) = 0$
(b) Ljung-Box test with H0: the forecast errors are independently distributed
(c) H0: No correlation between errors and predictions
P-Value for the whole period

Table 9: Tests on the VAR forecast errors

Nb. of cointegrating vectors (r)	Eigen -values	Trace	Trace*	Critical value	P-Value	P-Value*
0	0.458	89.09	72.90	57.32	0.000	0.001
1	0.375	48.05	40.56	35.96	0.002	0.015
2	0.219	16.54	15.17	18.15	0.084	0.127

Trace* and P-Value* refers to the Bartlett correction for small sample
H0: There are at most r cointegrating relationships

Table 10: Johansen trace test

VECM	Δ LOAN		Δ INV		Δ BLR	
	Coeff.	T-stat	Coeff.	T-stat	Coeff.	T-stat
$LRR1_{t-1}$	-1.671	(-5.938)	0.049	(1.130)	0.083	(1.984)
$LRR2_{t-1}$	-0.286	(-5.813)	0.009	(1.138)	-0.012	(-1.636)
$\Delta LOAN_{t-1}$	0.619	(2.694)	-0.027	(-0.745)	-0.074	(-2.185)
$\Delta LOAN_{t-2}$	0.337	(1.958)	-0.013	(-0.485)	-0.053	(-2.070)
$\Delta LOAN_{t-3}$	0.285	(2.435)	-0.005	(-0.270)	-0.007	(-0.408)
ΔINV_{t-1}	0.428	(0.484)	0.506	(3.673)	0.041	(0.316)
ΔINV_{t-2}	3.867	(4.219)	0.284	(1.990)	-0.287	(-2.113)
ΔINV_{t-3}	-1.773	(-2.028)	-0.169	(-1.244)	0.078	(0.604)
ΔBLR_{t-1}	-0.379	(-0.393)	-0.146	(-0.976)	-0.247	(-1.732)
ΔBLR_{t-2}	-0.800	(-0.959)	-0.076	(-0.587)	0.028	(0.224)
ΔBLR_{t-3}	-0.733	(-1.186)	-0.036	(-0.371)	0.033	(0.356)
$\Delta EURIBOR_{t}$	-0.339	(-0.980)	-0.055	(-1.012)	0.785	(15.295)
$\Delta EURIBOR_{t-1}$	0.001	(0.482)	-0.092	(-0.733)	0.320	(2.666)
$\Delta EURIBOR_{t-2}$	0.044	(1.176)	0.003	(0.263)	-0.100	(-0.945)
$\Delta EURIBOR_{t-3}$	0.070	(1.074)	0.067	(0.714)	0.003	(0.036)
$\Delta BOND_{t}$	0.377	(1.076)	-0.015	(-0.284)	0.126	(2.429)
$\Delta BOND_{t-1}$	0.104	(0.293)	0.036	(0.656)	-0.026	(-0.485)
$\Delta BOND_{t-2}$	0.206	(0.632)	0.043	(0.843)	-0.014	(-0.298)
$\Delta BOND_{t-3}$	0.379	(1.250)	0.041	(0.865)	-0.031	(-0.686)
Constant	-29.51	(-5.923)	0.801	(1.154)	1.502	(1.912)
R^2	0.668		0.544		0.915	
ARCH(4)	6.105	[0.19]	1.477	[0.83]	10.70	[0.03]
Normality	2.429	[0.29]	14.88	[0.01]	1.888	[0.39]
Weak exogeneity tests:						
$\chi^2(2) =$	19.7		6.31		6.34	
P-Value	0.00		0.04		0.04	
Multivariate tests for no residual autocorrelation:						
LM(1)	$\chi^2 = 11.16$	[0.38]				
LM(2)	$\chi^2 = 16.19$	[0.06]				

Note : Numbers in square brackets are P-Values.

Table 11: Estimated coefficients and properties of the VECM residuals

Series	Mean	Std Err.	Min	Max	Source
BLS Credit Standards	8.43	21.41	-18.20	77.10	Banque de France
BLS Access to fin. market	3.78	10.57	-22.40	35.10	Banque de France
BLS Banks' Liquidity	4.18	14.37	-20.90	51.20	Banque de France
BLS Economic activity	29.69	30.44	-13.90	100.00	Banque de France
BLS Corporate Business	29.54	27.81	-13.30	96.80	Banque de France
BLS Banks' Margins	-1.60	36.62	-73.20	86.00	Banque de France
BLS Banks' Margins on risky loans	28.50	30.03	-16.60	88.30	Banque de France
BLS Loan Amount	4.49	13.16	-23.50	42.00	Banque de France
BLS Collateral Requirement	3.38	17.83	-46.50	57.80	Banque de France
BLS Loan Duration	0.09	15.43	-28.30	47.30	Banque de France
BLS Demand for loans	-18.94	30.45	-86.00	45.90	Banque de France
BBB interest rate	4.61	1.25	1.93	7.70	Datastream
10-year OAT interest rate	3.55	0.68	1.96	4.48	Eurostat
Interest rate on covered bonds	3.55	0.82	1.33	4.99	Datastream
Capital-to-asset ratio	5.97	0.45	5.29	6.82	ECB
Liquidty-to-asset ratio	11.27	1.38	8.15	12.79	ECB
Default probability of NFC	2.03	0.86	0.93	3.77	ECB
Expected Default Frequency of NFC	0.74	0.54	0.17	2.15	Moody's
Expected Default Frequency of Banks	0.57	0.92	0.03	3.57	Moody's
CDS Premium (Index for France)	154.87	152.60	8.14	503.53	ECB
Asset Swap Spread (All, non-financial)	92.53	54.31	26.00	276.00	Merrill Lynch
Asset Swap Spread (BBB non-financial)	137.16	80.27	38.00	397.00	Merrill Lynch
Spread covered	0.00	0.28	-0.62	0.77	Author's calculation
BBB Spread	-0.62	0.84	-3.69	0.24	Author's calculation
SRISK (Index for France)	160.01	107.57	29.09	313.74	V-Lab
Composite Indicator of Systemic Stress	0.24	0.19	0.04	0.74	ECB
LTRO (on GDP)	0.16	0.13	0.02	0.45	ECB
ECB balance sheet's SIZE (on GDP)	0.72	0.27	0.42	1.30	ECB
LTRO quarterly growth rate	10.11	30.12	-55.89	105.28	Author's calculation
SIZE quarterly growth rate	2.81	9.15	-13.38	34.56	Author's calculation
Housing price quarterly growth rate	6.14	7.27	-9.04	15.99	Banque de France
CAC40 quarterly growth rate	0.91	7.65	-23.17	10.33	Datastream
Term Spread	1.43	0.96	-0.49	2.82	Author's calculation
Std. error of CAC40	310.14	178.33	82.69	806.40	Author's calculation
VCAC (max. value over the quarter)	30.49	12.42	13.78	78.05	Datastream
MIX	0.15	0.02	0.10	0.18	Author's calculation
GOOGLE T1 ('cash credit')	24.58	32.87	0.00	100.00	Google, Author's calc.
GOOGLE T2 ('short financing')	10.71	28.71	0.00	100.00	Google, Author's calc.
GOOGLE T3 ('short run credit')	8.69	23.75	0.00	100.00	Google, Author's calc.
GOOGLE T4 ('extended payment terms')	25.10	21.34	0.00	100.00	Google, Author's calc.
GOOGLE T5 ('loans for SMEs')	20.61	31.15	0.00	100.00	Google, Author's calc.

Note: statistics over the period 2003 Q1 - 2013 Q3.

Table 12: Descriptive statistics and source of the additional indicators Z

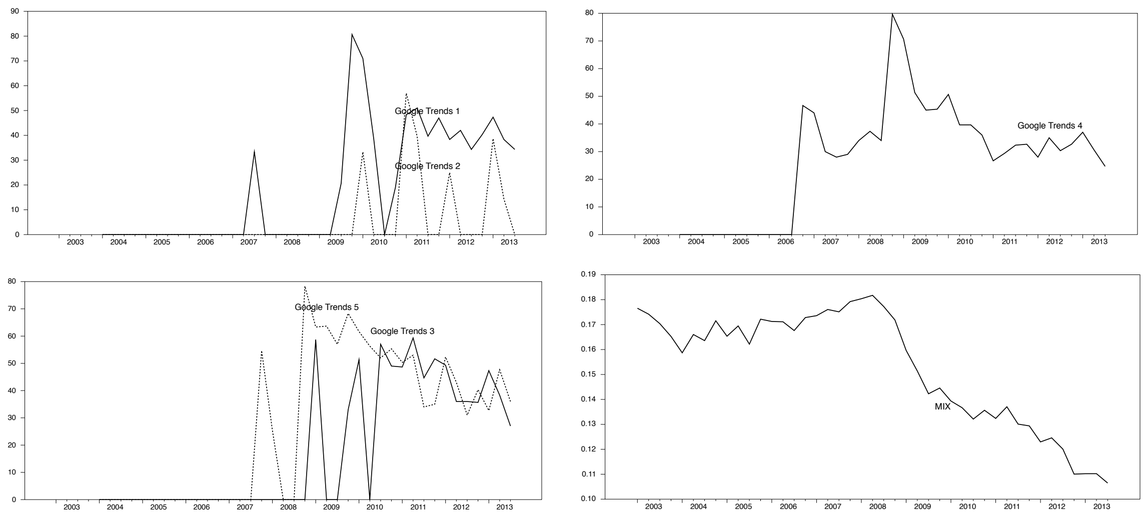

Figure 7: Selected additional indicators

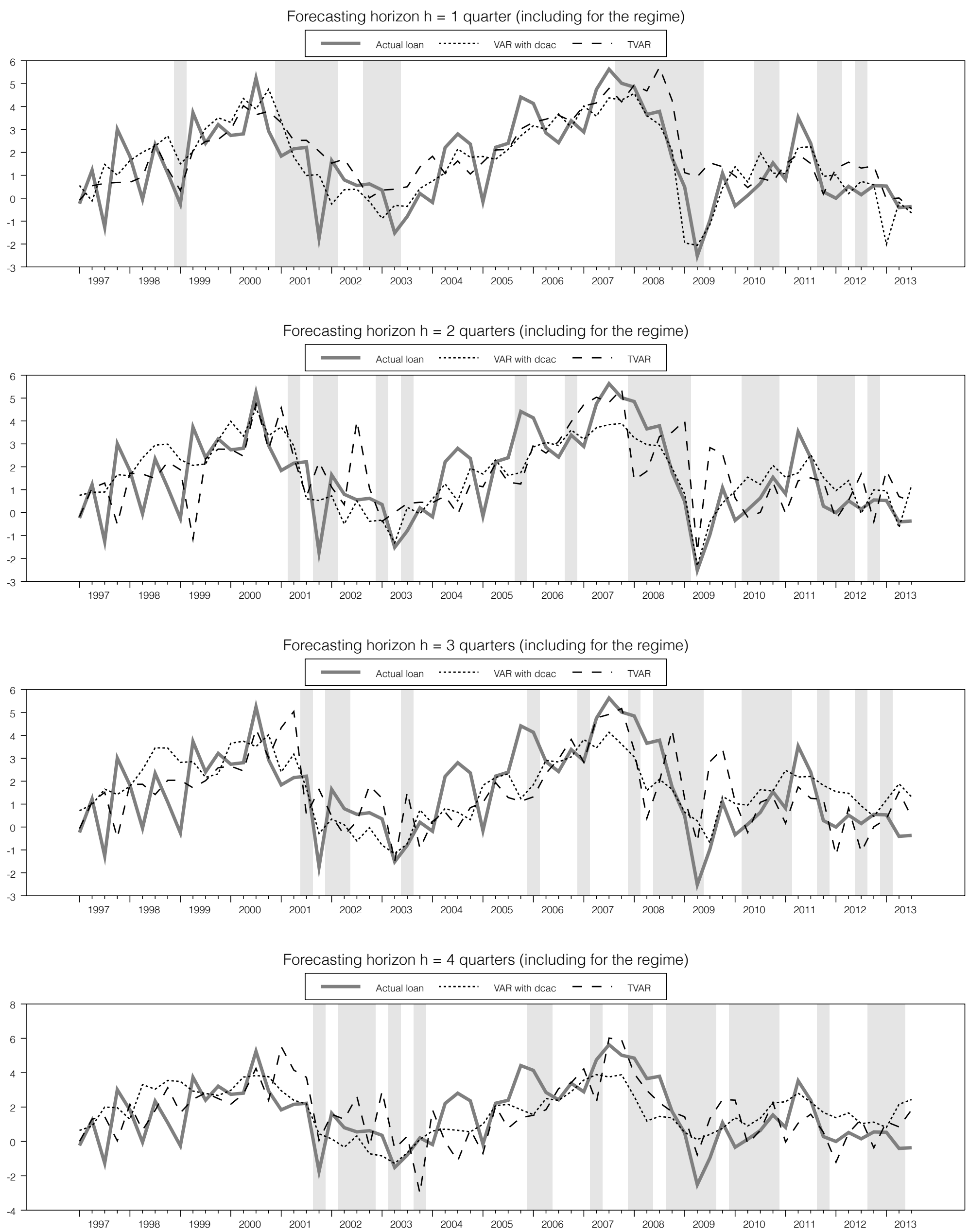

Figure 8: TVAR with endogenous regime forecast *vs* Augmented VAR

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