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No evidence of financial accelerator in France

Abstract

In this paper, we investigate the role of financial acceleration phenomena in France over the period 1987-2013. Constructing a threshold-VAR model allowing for two credit regimes, we formally test for the presence of a financial acceleration and present generalized impulse response functions. Using the volatility of the French stock index CAC40 and the lending spread between small and large firms as credit stress indicators, we show weak evidence of the existence of a global financial accelerator in France and also provide a simple method for computing contributions in threshold-VAR. We insist on the difficulty to construct stable financial sphere - real economy interactions models for France or to identify adequate credit stress indicators.

Keywords: credit constraint, flight to quality, generalized impulse response function, threshold VAR (TVAR)

En France, l'existence d'un accélérateur financier n'est pas établie

Résumé

Cet article étudie le rôle de l'accélérateur financier en France durant la période 1987-2013. À l'aide d'un modèle VAR à seuil autorisant la bascule entre deux régimes de crédit, nous testons formellement la présence d'un effet d'accélération financière et présentons des fonctions de réponses généralisées. Selon deux mesures des conditions de crédit, la volatilité du CAC40 et le spread bancaire à l'emprunt entre petites et grandes entreprises, nous obtenons un rôle faible de l'accélérateur financier en France. Nous proposons aussi une méthode simple pour le calcul des contributions dans un modèle VAR à seuil. Enfin, nous insistons sur la difficulté à construire des modèles stables d'interactions entre les sphères financières et réelles en France ou à identifier des indicateurs des conditions de crédits adéquats.

Mots-clés : contraintes de crédit, fuite vers la qualité, fonction de réponse généralisée, VAR à seuil (TVAR)

Classification JEL : C15, C32, E32, E51

Introduction

The 2008 global crisis has refocused interest on macro-financial linkages, and in particular on the role of financial intermediaries and their ability to properly finance the economy. In the wake of the financial crisis, numerous European banks experienced high stress periods. Capital shortfalls and liquidity restrictions temporarily led to dramatic drops in interbank lending and called for actions from both the member States and the monetary institutions of the Eurozone.

Consequently, corporate credit in Europe - and in particular in France - has seen a sharp contraction. This decline is partly due to a fall in credit demand from companies. Faced with a collapse in output demand and what was initially a pronounced increase in uncertainties as to future economic growth, companies sharply cut their investment spending and scaled down their inventory, resulting in a fall in their demand for financing.

But the decline in credit may also be partly due to the credit supply behaviour of banks. In addition to tighter prudential requirements by national supervisors, the deterioration in the creditworthiness of borrowers may have led banks to restrict their credit supply, amplifying the economic downturn.

The latter phenomenon refers to the concept of the financial accelerator, as first introduced by Bernanke and Gertler (1989) [6] and Kiyotaki and Moore (1997) [15]. When the short-term economic situation is poor, the value of assets held by companies and the profitability of their use tend to fall, thereby increasing the risk for a bank of not getting its funds back when it grants a loan. Banks are therefore less conducive to the distribution of credit when the short-term economic outlook is poor and when prudential requirements are being tightened. This theoretical prediction question the importance of financial acceleration phenomenons and their role during the recent crises in France.

This paper makes an attempt to assess the extent to which financial accelerating effects have been at work over the last decades in France, with a special focus on the Great Recession and its aftermath. While numerous papers provide a microeconomic partial equilibrium assessment of the impact of supply-side effects on credit markets (see for instance Kremp and Sevestre (2013) [17] or Cabannes et al. (2013) [8]), we provide with a macroeconomic general

equilibrium analysis.

The non-linear nature of the financial accelerator lends itself well to the estimation of a threshold model. Following the methodology developed by Balke (2000)[3], we estimate a threshold vector autoregressive model (TVAR) with two economic regimes depending on credit conditions over the period 1987 - 2013. The switch between these two regimes is endogenously determined, and therefore allows for a richer description of mechanisms at stake during high credit stress periods.

The two estimated models include four variables: a measure of output (GDP), a measure of inflation (growth rate of Consumer Price Index), a measure of lending interest rates and a measure of credit conditions. For the latter, we study two different sources of credit instability: either a *financial markets stress* measured by the volatility of the CAC40 index, or a *flight to quality* phenomenon measured by the lending spread offered by banks between small and large firms. The volatility of the CAC40 index is considered a measure of the uncertainty surrounding the valuation of firms by credit markets, including bank credit markets, whereas the lending spread reflects the increase of risk adversity of banks during bad times. Therefore, those measures provide a convenient way to measure the extent to which financial acceleration may be at work.

The formal validity of this non-linear modelling approach is tested following Hansen (1996) [13] methodology, and the impulse responses of variables to shocks are computed using Generalised Impulse Response Functions as described in Koop, Pesaran and Potter (1996) [16].

As a result, by means of comparison of the two models, we draw interesting conclusions about the existence and the strength of the financial accelerator in France over the period of interest. Formal likelihood ratio tests in our first model based on the volatility of the CAC40 index argue for the absence of non-linearities in the relationship between credit and macroeconomic activity, and is therefore restricted to a linear model. On the contrary, the second model reflecting the *flight to quality* phenomenon pleads for the existence of a financial acceleration effect, and highlights three main periods of *flight to quality* in the 2000's, namely 2002Q3-2004Q3, 2009Q1-2011Q1 and 2012Q2-2013Q3, corresponding to observed credit contraction periods. However, the study of the impulse responses shows that the expected asymmetries in responses across credit regimes are absent in our models. The estimated threshold appears to separate our sample in almost two identical halves for each credit regime. As a conse-

quence, in absolute terms, the role of the financial accelerator seems to be limited in France over 1987-2013.

Moreover, as an innovation to the literature, we propose a simple lower bound estimate to the cost of credit shocks for economic activity, and apply it to the 2008 financial crisis period and onwards. Computing the GDP growth dynamic simulation for both models in the presence of all observed shocks excepting credit conditions fluctuations, we conclude to a cumulated cost of credit conditions fluctuations since 2008 ranging from 0.5 p.p. for *financial markets stresses*, to 2 p.p. of GDP growth due to *flight to quality*. These same flight to quality phenomenons during the 1992 crisis accounted for an identical and stable over time 2 p.p. cumulated cost for economic growth. Whereas financial accelerating effects do not dominate in France when studied from a global time prospect, the particular chronology of adverse shocks in 2008 and onwards indeed induce non-negligible credit regime switches, further depressing economic activity.

These results seem in line with those of Calza and Sousa (2006) [9]. Actually, whereas Balke (2000) [3] identifies important non-linear shock propagation effects in the US, Calza and Sousa show weaker evidence of these non-linearities on aggregate European data over the period 1981-2002. However, we show that these conclusions remain fragile, providing with a detailed analysis focusing in particular on the choice of input variables, their construction and their transformation. Across all model specifications, obtaining a *well-behaved* model, both in terms of econometric and economic properties, is a rather difficult task. In particular, only a few number of models provide Impulse Response Functions conform to economic intuition. As a result, estimations presented in this paper correspond to the specific selection of such a *well-behaved* model. Therefore, we highlight the difficulties arising in the construction of a financial-real sphere interaction model aimed at capturing financial acceleration effects in France. In all, our results may advocate for the absence of a financial accelerator in France over the 1980-2013 period. These results may also reflect that traditional transmission channels of financial shocks are irrelevant for France.

This paper is organized as follows. In the first section, we review empirical and theoretical evidence of the existence of supply-side effects and financial accelerators. In the second section, we present our dataset. In a third section, we describe the econometric TVAR methodology aimed at modelling financial accelerating effects. The fourth and fifth sections present the main results of this study and a robustness discussion.

1 A fragile financial context within weak European economies

Before the analytical part of this paper, we first give a brief summary of the events that occurred in the Eurozone after 2008 and that lead to deteriorated credit and economic environments.

1.1 Market fragmentation: the end of Euro-wide studies

Despite the slow recovery of the Eurozone from recession in 2013, credit markets continued to contract in 2014: outstanding credit to non-financial enterprises was down by 2.0% year-on-year in the third quarter of 2014. This contraction, which has been almost uninterrupted for close to 5 years, is directly linked with the two spells of recession in the Eurozone in 2008-2009 and then 2011-2013. Among other things, the latter led to a fall in the investment spending of companies, and therefore in the drying up of demand for credit to banks. However, this fall in credit demand, when considered in the general framework of perfect financial markets, may not be sufficient to explain by itself the overall economic situation: firstly because large contrasts in the access to credit remain between the different members of the monetary union, secondly, while some Small and Medium Enterprises still declare having trouble to access financing, some large companies moved towards to market financing. Moreover, this credit demand drying up remains insufficient to explain the time-persistence of the adjustment long after the Eurozone emerged from recession, and its specificities across countries.

Actually, during the third quarter of 2014, credit fell by almost 10% y-o-y in Spain, while it grew in France by 2%. Looking at the Survey on Access to Finance of Entreprises (SAFE) conducted by the European Central Bank (ECB) among small and medium-sized companies in April 2014 (see Figure 1) also confirms this heterogeneous access to bank financing. While only 11-12% of French and German firms surveyed in 2014 faced credit restrictions[1], 20% of Spanish and Italian were still facing difficulties in the access to credit.

This contrasted situations and fragmented credit markets therefore argues for macroeconomic studies at the national levels.

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[1]In the SAFE survey, we consider that a firm faced credit restrictions either in price or volume, if (*i*) it did not apply by fear of rejection (self-censorship), (*ii*) applied but was rejected, (*iii*) applied but refused because the cost was too high or (*iv*) applied but got only a limited part. This is a crude measure of credit restrictions and credit can indeed be restricted by banks because of a proper assessment of the weak financial health of some firms.
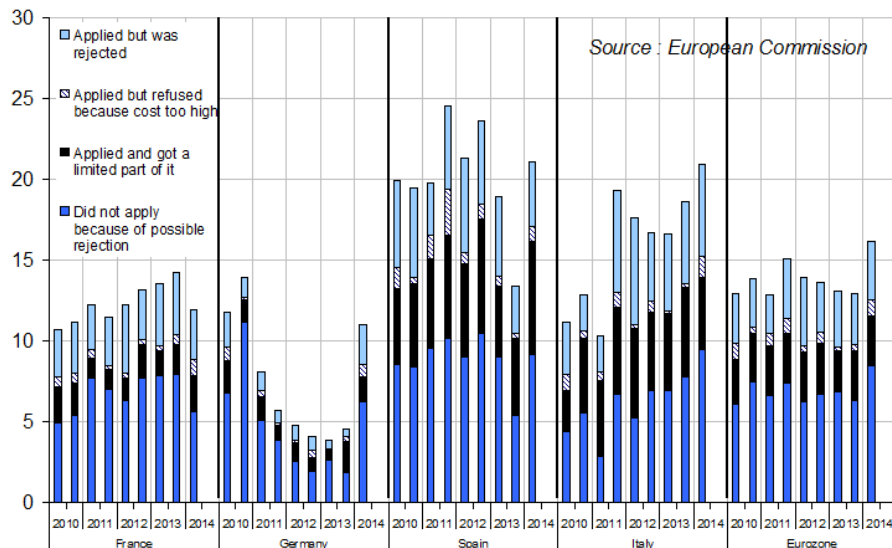
Figure 1: Bank credit difficulties for Small and Medium Enterprises
(SAFE survey)

1.2 2008 to today, a brief Eurozone summary

Understanding the importance of the credit market adjustments requires to shed light on market imperfections that have arisen before and during the Great Recession. This fall in credit indeed contrasts with the pre-crisis period. During the first half of the 2000s and through to 2007, the credit market went through a phase of massive expansion in the major Eurozone countries, mainly driven by economic growth, but also supply-side phenomenons, for instance a poor perception of systemic credit risk by European banks. In the wake of the subprime crisis that started in 2007 in the United States, the risk carried by banks that had granted loans to insolvent borrowers began to materialise with the growing level of borrowers' defaults, causing a sudden turnaround in expectations. The European credit market suddenly stalled, before contracting in a process that persists today (see Figure 2).

Despite the ECB reaction and falling refinancing rates, easing monetary conditions have passed on in different ways to the countries of the Eurozone. The very fragile state of the banking system of certain peripheral countries, such as Spain, where the banks were highly exposed to real-estate risk, prevented the full transmission of the ECBs' low-rate policy. On the contrary, it was passed on more clearly to corporate lending rates in countries perceived as being sounder, such as France and Germany. Systemic risk was also reinforced by the high correlation between sovereign risk and banking risk highlighted by the sovereign debt crisis
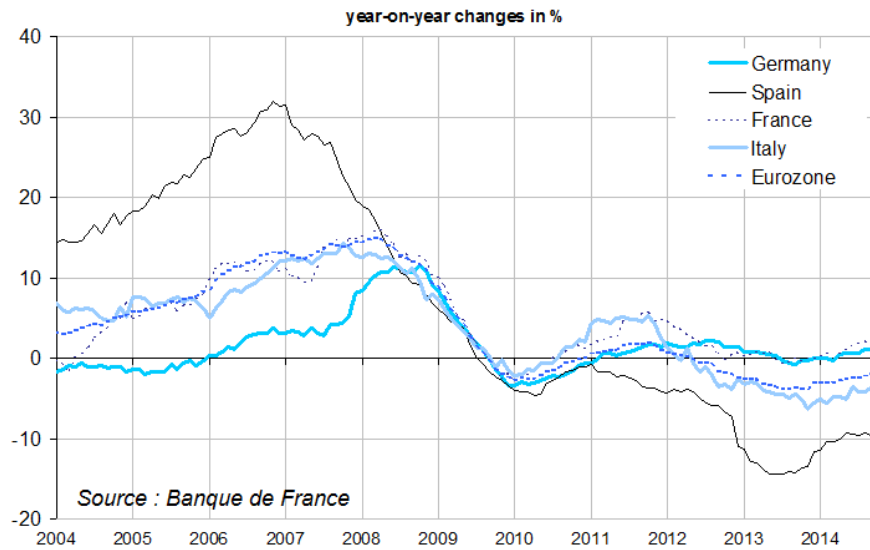
Figure 2: Annual growth rate of outstanding loans to non-financial companies

from 2010 onwards. This situation whereby each nation carries a specific risk premium has led to the fragmentation of the credit market. For example, the borrowing costs faced by non-financial firms continue to be much higher in those countries perceived as being more fragile (see Figure 3).
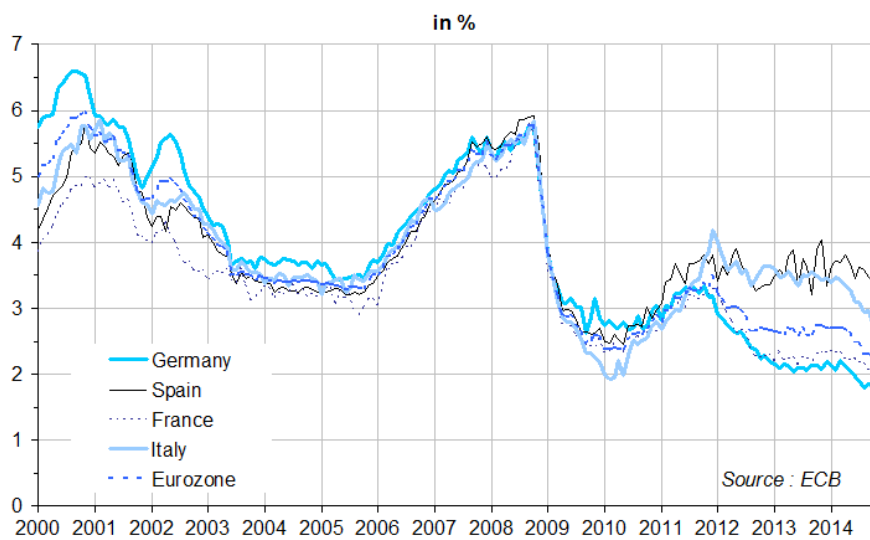
Figure 3: Average bank rate on new business loans to Eurozone firms

In consequence of growing difficulties of the national banking systems the structure of corporate financing in the Eurozone evolved toward more market oriented solutions. Indeed, unlike American companies relying more directly on financial markets and in particular bond issues, the majority of European companies gain access to external financing through bank intermediation. In particular in France, bank lending represented about 73% of the total debt of companies prior to the crisis. Since 2008, this share has regularly fallen and bank credit now represents 63% of companies' external financing.

The origin of this substitution lies in the financing difficulties of the banking system and the fall in the rates on bond issues, generating opportunistic behaviour. It is hitting companies in varying ways. While the lowest-risk companies (generally large companies) can achieve this substitution at a low cost, the same fact does not apply to companies perceived by markets as being of higher risk (usually smaller companies), whose bond rates incorporate a higher-than-usual risk premium that persists today.
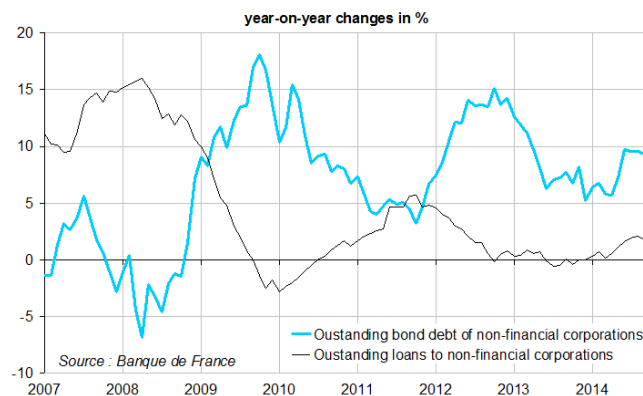
Figure 4: Debt structure of large French firms

For large companies that enjoy easier access to financial markets, the fall in bank credit supply has indeed been offset by a substantial rise in debt security issues (see Figure 4). In France, market debt progressed by 15% in 2009, after a 1% fall in 2008. At the same time, bank financing fell from a growth rate of 13% in 2008 to 3% in 2009. The same quasi-substitution phenomenon can be observed between the end of 2011 and 2012, in the wake of the sovereign debt crisis, due to a threatening liquidity crunch at the time.

On the opposite side of the spectrum, and as mentioned above, around 15% of European SMEs declared having difficulties gaining access to bank financing in 2014. These contrasted situations between firms however share a common feature of a voluntary or imposed (partial) renunciation to bank intermediated credit markets, and raise a key question: do those constraints have a share of responsibility in the birth of recessions and/or their slow subsequent recoveries?

1.3   Literature review: credit supply constraints in the Eurozone

Mild microeconomic evidence of credit supply constraints in the Eurozone   Regarding the first question, several studies have been conducted at the microeconomic level in the Eurozone in recent times. Globally, they reach similar conclusions and tend to show the absence of credit rationing through to 2010.

Working on two microeconomic databases (FIBEN and LiFi)[2] on individual SMEs, Kremp and Sevestre (2013) [17] show that there is no robust evidence of small companies having been subject to credit rationing between 2008 and 2010 in France: although the banks idiosyncratically reduced their credit supply, the decline in lending to small companies was mainly due to a fall in demand in the wake of shocks on activity. Likewise, Cabannes et al. (2013) [8] conclude that the deteriorated outlook predominated over any credit restrictions there might have been for French companies. The economic part of the French 2008/2009 fiscal stimulus was particularly targeted at helping SMEs and might explain this assessment. Besides, this absence of credit constraints during the crisis might have been explained by a more intensive use of existing and available credit lines.

In the case of Italy, Del Giovane, Eramo and Nobili (2011) [12] use the data of the Bank Lending Survey (BLS) combined with micro-level information on loans to the private sector to address the question of credit constraints during the 2002-2009 period. While restrictions on supply did have a certain impact, they conclude that pure supply effects[3] were of minor importance over the period 2007-2009.

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[2]FIBEN represents balance sheet data, whereas LiFi exposes financial linkages between French firms.

[3]Following the authors' definition, this category includes constraints arising from both the central bank and the supervisory authority and therefore not related to firms' economic and credit worthiness. In particular, this relates to the cost of funds and balance sheet constraints for banks.

In Germany, Rottmann and Wollmershäuser (2012) [20] also conclude that there was no real credit rationing in 2008-2009. On German Ifo Business Survey data from mid-2003 to the end of 2010, they construct a credit crunch indicator, as the part of loan supply not explained by firm-specific factors (firms' creditworthiness) and the safe interest rate (opportunity cost of providing risky loans). They find lower evidence of credit crunch in Germany during 2008-2010 than during the period 2003-2004. Interestingly, they also find that large firms were the most affected one at the beginning of the financial crisis.

Lastly, concerning Spain however, Bentolila et al. (2013) [4] developed a different approach based notably on detailed data regarding relationships between companies and their banks, and find some evidence of credit rationing. In particular, this rationing appears to be significantly more severe when financing was taken out from a bank that was hit harder by the crisis (for instance the savings banks, *Cajas de Ahorros*).

Even though these studies mainly reject the idea of pure supply effects at the microeconomic level, the weak recovery observed in the Eurozone still leads us to question the importance of financial and credit markets for economic activity. Indeed, these microeconomic papers are subject to caveats. For instance, these papers often fail to account for firms' demography and in particular bankruptcies during the crisis that might have created a selection bias at the micro level when looking at firms' access to credit. More generally, at the macro level we refer to a looser definition of credit constraints encompassing both credit volumes and borrowing costs restrictions, without disentangling both, as a more adverse credit environment likely to induce macroeconomic effects.

In the end, the weakened financial situation of banks over the last six years may have adversely affected their global credit supply behaviour and induced a slower recovery.

Financial acceleration effects Two streams of economy theory address this question and provide insights into the mechanisms involved: the financial accelerator theory and the *flight to quality* phenomenon. These mechanisms imply that endogenous forces in credit markets amplify and propagate shocks to the real economy. Based on strong microeconomic foundations they conduct to differentiated macroeconomic regimes.

The roots of both mechanisms lie in financial market imperfections. Bank financing involves lenders and borrowers in principal-agent relation as described by contract theory:

lenders and borrowers do not share the same information concerning the degree of risk attached to the investment projects, relating as for instance to the behaviour of the borrower or the final returns of investment projects. This information asymmetry is a credit market imperfection. Banks consequently implement systematic auditing and information collection procedures to estimate the potential value and the potential risk bound to the contract. These procedures are costly and are therefore passed on by the banks to their clients in their credit access terms: it gives rise to an external financing premium.

To minimize information asymmetries, along with the counterparty risk, lenders can base their decisions on the value of the assets held by the borrowers, and accordingly apply an inversely-proportional external financing premium. Signals used by banks to infer risk may come from the balance sheet net worth of companies or their collateral level. However, as the valuation of balance sheets or collateral is correlated with economic activity, the banks introduce a *de facto* pro-cyclical mechanism in their loan granting.

Therefore, a first stream of literature introduces financial frictions by capturing firms' balance sheet effects on investment in a situation with costly state verification. This setting allows endogenous determination of the external finance premium, *i.e.* the difference between the cost of external funding and the opportunity cost of internal funds. Bernanke and Gertler (1989) [6] develop a simple neoclassical model of business cycles where borrowers' balance sheets/*credit-worthiness* condition firms' production dynamics. A higher borrower's net worth[4] reduces agency costs of financing real capital investments by weakening information asymmetries. In response, business upturns, improving net worth and further lowering agency costs, therefore increasing investment. In the end, this amplifies activity. In economic slowdown periods, the deterioration of the balance-sheet position of agents results in an increased premium and more generally, in a deterioration of lending conditions. As a result, companies are then forced to limit their investment expenditure, and hence their level of production: the initial shock spreads and grows. In other terms, shocks affecting the net worth can initiate fluctuations in idiosyncratic production.

A second approach introduces collateral loans and durable assets as signals for banks, therefore focusing on the role of asset prices. Kiyotaki and Moore (1997) [15] perform a general equilibrium analysis and develop the idea that production factors (real-estate assets, plant, etc.) may serve as collateral for loans. In their model, the borrowing ceiling corresponds to an

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[4]As measured by the difference between assets and liabilities.

exogenous fraction of the value of collateral. When the price of assets falls, the increased difficulty in obtaining financing leads to a drop in investments further depreciating the value of collateral assets at the general macro equilibrium. Hence, the interaction between credit limits and asset prices turns out to be an important amplification and propagation mechanism of shocks at the aggregated level. A shock on the price of assets may generate a variation in the value of collateral and hence trigger the mechanism described above. Here again small, temporary technology or income shocks might generate large, persistent fluctuations in aggregate output and asset prices.

These mechanisms known as financial accelerators, or *broad credit channel*, explain the interdependence between the real and financial sectors. In order to identify those phenomenons at the macro level, two additional comments need to be made with respect to the form that financial accelerator take place in the economy. First, banks may adopt differentiated behaviours depending on the size of companies, a phenomenon known as the *flight to quality* and first exposed in Bernanke (1993) [5]. Second, the significance of the financial accelerator mechanism differs according to the phase of the economic cycle.

As explain above, a risk premium appears to compensate lenders for the costs incurred in evaluating, monitoring and enforcing credit contracts. Therefore, banks usually reduce the proportion of funds allocated to uncertain projects requiring close monitoring (or increase their cost of financing) and tend to favour safer projects. During a global increase in uncertainties (as during crises), information asymmetries are potentially smaller for large enterprises, and banks will consequently favour those firms' projects both through a lower borrowing cost or higher credit volumes, restricting their lending to small firms. This differentiated treatment comes from structural difference between small and large firms: large firms usually operates in different sectors and offer a greater risk diversification. Moreover, they are also less sensitive to economic fluctuations as they have better control over their inventory. Large firms also generally have officials (accountants, auditors) who allow banks an easier access to information, leading to economies of scale in the information collection process and agency costs borne banks. Last, this same firms are often in relationship with multiple banks, and are therefore relatively more financially stable.

A second remark stems from the fact that financial accelerating phenomenons have a stronger effect in *bad* times than in *good* times. During an expansionary phase the global net worth of borrowers, at aggregated level, is high and hence the agency costs are low. Conse-

quently, the external financing premium is low and variations in the value of companies have little effect on the lending decision and the financial accelerator is weakened. In recessionary periods however, when global wealth is low, fluctuations in current profits have significant effects on investment and production. As a result, the financing premium increases and the amplifying effects are therefore stronger in unfavourable economic periods. This difference may amplify the *flight to quality*, large enterprises being able to dampen a depressed activity more easily. This idea is exposed in Bernanke, Gertler and Gilchrist (1994) [7]. In all, the asymmetric nature of the financial accelerator stems from the zero lower bound on the external financing premium. Indeed, in bad times this premium might potentially climb up to high levels, restraining economic activity, whereas in good times, it cannot decrease below 0 and further foster growth.

The financial accelerator is thus asymmetrical in essence and potentially displays non-linear behaviours as to the response of real activity to economic and financial shocks. The methodology developed hereafter and the variables used attempt to identify these differentiated regimes. Moreover, all these theoretical approaches share a common critical feature: credit conditions are not a necessary source of shocks but plays, nonetheless, the role of propagator and amplifier of shocks.

Identifying credit constraints and their macroeconomic impact As exposed above, the existence of credit constraints is not a necessary condition to justify the importance of credit for activity and theoretical works also suggest that the economy might react differently depending on the credit environment.

To investigate the existence of *flight to quality* effects, Balke (2000) [3] introduces the use of a Threshold-VAR and studies the non-linear propagation of shocks in the economy conditionally on the credit environment. Working on US data on the period 1960Q1-1997Q3, Balke measures credit conditions with three different *flight to quality* indicators namely: (*i*) the commercial paper/T-Bill spread, (*ii*) the mix of bank loans and commercial paper in total firm external finance and (*iii*) the difference between the growth rates in the short-term debt of small and large manufacturing firms. He finds evidence of non-linearities in the propagation of shocks depending on the credit environment and notices that shocks have stronger effects on GDP and inflation when credit is in a *stressed* credit environment[5].

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[5]Balke identify this *stressed* credit environment to a regime of credit constraints.

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Proceeding identically, on aggregate European data over the period 1981Q1-2002Q3, Calza and Sousa (2006) [9] measure credit conditions by the growth rate of loans to the private sector. They also identify non-linear propagation phenomenon and magnified effects during low credit cycles. However, these results were estimated on the pre-crisis period and may not apply to the credit environment yielded by the 2008 financial crisis and onward. Banking systems of the different EU countries have indeed proved to lack stabilization mechanisms.

This paper replicates these methodologies on French data including the 2008 crisis period.

2 Data

This section presents the dataset used for the empirical analysis. However, as the choice of these data is subject to numerous caveats, the sensibility of the results to this choice is discussed in Section 5.

Disentangling credit supply and demand effects: Disentangling between credit supply constraints and credit demand contractions is a difficult task at the macroeconomic level. As this paper makes an attempt to mainly focus on the credit supply side, a few introducing warnings need to be raised:

- a negative credit supply shock might both refer to a transmission of banks' idiosyncratic constraints (balance sheets issues, difficulties to access interbank lending markets, macroprudential regulations), but also to a proper assessment of the deteriorated counterparty risks and firms' financial health,

- in case of credit standards tightening, firms might self-censor and decide not to ask for credit. As a result, part of the potential credit demand is unobserved at the macro level,

- corporate bonds markets are not necessarily a *pure* substitute to credit, as Cecchetti (1995) [11] brings to attention that in the US, bond financing might be conditional on the availability of adequate credit lines in order to convince investors,

- credit constraints are differentiated by firms' size, small firms being more sensitive to them as they have fewer substitute sources of financing. Aggregate data might therefore hide this underlying heterogeneity of firms.

Lastly, the general choice of credit stress variables in our analysis was partly driven by availability issues. Financial and country-specific data are difficult to obtain on long periods,

especially before the creation of the Monetary Union. In the end, our dataset is still subject to finite sample bias.

Dataset: Our dataset consists of four macroeconomic variables: a measure of economic activity, of inflation, of lending interest rates and of the credit environment.

Economic activity is measured here by the growth rate of the Gross Domestic Product. Inflation is measured by the growth rate of the French Consumer Price Index. Those data are taken from the Quarterly National Accounts and statistics of the Insee[6] and are available at minimum for the period 1952-2013.

The interest rate corresponds to the financing cost of firms in the economy, in order to study its impact on economic activity. It is measured by the average interest rate on loans (excluding overdrafts) of more than two years computed by the Banque de France on 1984-2014.

Lastly, the model contains a variable intended to reflect the credit market situation. Credit constraints cannot be directly observed or quantified and several indicators attempt to identify their consequences. We choose to identify here two phenomena: *flight to quality* episodes or more general *credit squeezes*. The analysis therefore uses two different measures of credit conditions. Note that responses to the BLS survey have not been used as indicators due to their biasedness and their differences with the SAFE survey.

The first variable used to assess the existence of *flight-to-quality* phenomenons is the difference between the loan interest rate billed to small enterprises and that billed to large enterprises.

The theory exposed in previous section, based on differences in agency costs and on the uncertainties surrounding the projects of large and small enterprises, indeed suggests that banks apply an external financing premium that differs according to company size, even though the refinancing cost on loans is the same for both type of firms. The interest rate spread indeed captures this effect as it tends to widen during periods where bank credit is tightening. A structure effect could however reduce this difference if a proportion of small companies did not take out these loans which have become more costly. The riskiest loans would be granted relatively less often, bringing down the average rate overall and probably more for small en-

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[6]French National Institute for Statistics and Economic Studies.

terprises.

Due to a lack of long time series on interest rates filtered by company size, it is necessary to use an approximation in order to build this indicator. Therefore, the loan amount is used as a proxy for size. We use Banque de France interest rates data between 1984 and 2013 on credits (excluding overdrafts) of less than two years. The rates on loans agreements for less than €15 thousands are considered as being granted mainly to small enterprises, while the rates for loans above €1.5 million are considered as being granted mainly to large enterprises. This breakdown by company size, which is regularly used in the empirical literature, is an approximation of the partition between "more secure borrowers", i.e. large companies, and "riskier borrowers", i.e. small companies. Lastly, as these interest rates are end-of-period measures, we choose to lag the time series by one quarter, in order to obtain a series representing the choice of banks at the beginning of the current period (i.e. the decision at the end of the previous quarter). This relates to our choice of ordering as discussed in the next Section 3.

As well as its *a priori* ability to capture *flight-to-quality* periods, this measurement presents the advantage of being relatively independent of the economic cycle and of monetary policy decisions. Indeed, in a "standard" economic regime the behaviour of banks towards borrowers should evolve in an undifferentiated way between the various sizes of company. For example, in an economic recovery period, banks will increase their flows of new loan agreements at the same speed across all companies. Similarly, when the ECB's base interest rates are cut, banks will pass this reduction on identically to small and large enterprises. On the contrary, by capturing the differentiated ex-post behaviour of banks towards different company sizes, these indicators mainly identify the credit supply side of credit squeezes. However, like any indicator, they can also take account of a differentiated behaviour by the companies themselves, and, in this particular case, a differentiated behaviour among large companies, who would attempt to replace bank financing by market financing.

A last variable completes this identification of credit stress phenomena by identifying bank credit squeeze phases, that is, a deterioration of the financial environment which may have an impact on the credit behaviour of banks.

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A measure of stock-market volatility of the CAC40 index[7] is used, measuring conditions on the financial markets. As the CAC 40 VOLA IDX volatility index in the option market, that is usually used for measuring financial uncertainty, is not computed on long time series, we turn to the alternative measure of the volatility of the index by its quarterly relative standard error.[8] This also allows us to obtain a measure of market uncertainties on the period 1987-2013.

This measure allows us to focus more specifically on credit squeezes arising from financial markets uncertainties. As the volatility of the stock market is an indirect measure of risk aversion and of uncertainties as to the future economic situation of firms (or of the whole economy and the associated output demand), it is tied to uncertainties surrounding the valuation of companies' balance-sheet. In the light of the previous section and of the *net worth* channel, this results in a higher information asymmetry for banks unable to properly assess the risk associated to a given loan project. This directly translates in a credit tightening for all types of firms.

Series transformation: The choice of transformation applied to each variable depends on the stationarity properties of the data and their homogeneity. For credit conditions variables, we also consider an additional criterion of their econometric ability to give *well-behaved* results. We detail this *well-behaved* criterion in the robustness section 5.

As a result, we choose to work on the growth rate of GDP and CPI and on the first differences of the interest rates for the main macroeconomic variables. For the lending rate spread, and the volatility of the CAC40 index, we retain the first difference of the lending spread and the level of the volatility.

The variables in the dataset are plotted in Figures 5-10.

3 Threshold Vector Autoregression

We now present the methodology used to question the existence of credit constraints and non-linearities in the economy at the macroeconomic level. In other terms, we are interested in knowing how does the French activity respond to the credit environment?

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[7]The CAC40 is the French benchmark stock market index. This index represents a capitalization-weighted measure of the 40 most significant values among the 100 highest market caps on Euronext Paris.

[8]On daily data, we compute the quarterly standard error to quarterly average level ratio in order to correct for differences in the CAC40 level across time.
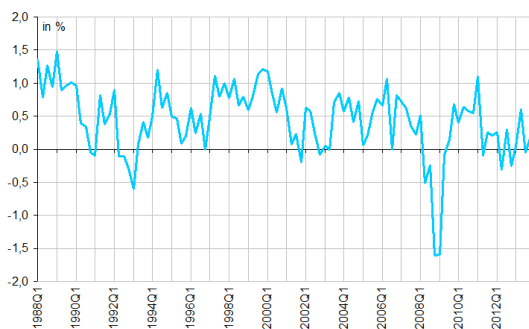
Figure 5: Real French quarterly GDP growth
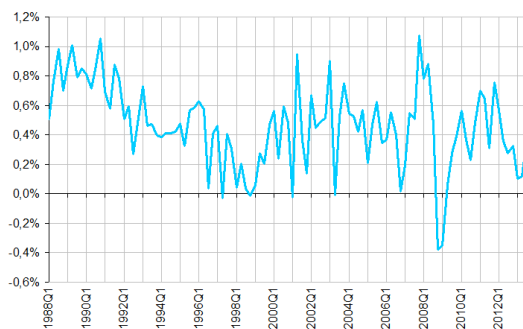
Figure 6: French quarterly CPI inflation
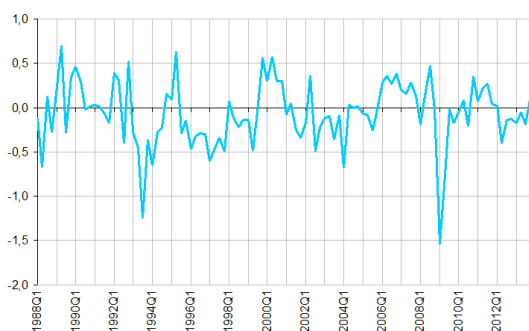
Figure 7: Interest rates on loans of more than two years
(in first differences)
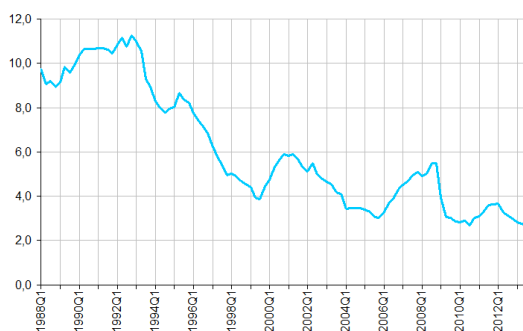
Figure 8: Interest rates on loans of more than two years
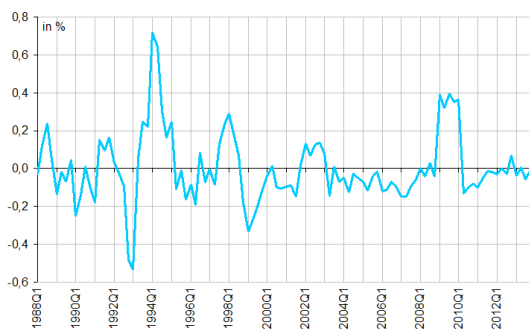
Figure 9: 5-th order moving average of the lending rate spread between small and large firms (in first differences)
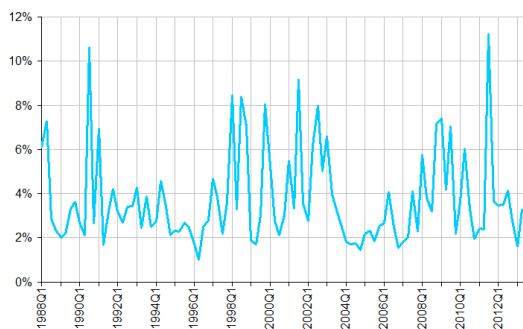
Figure 10: Volatility of the CAC40 index

3.1 Threshold-VAR

To identify a potential non-linear propagation of shocks in the economy, we turn to a Threshold-VAR (henceforth TVAR) model as exposed in Balke (2000) [3].

Although non-linearities are *a priori* a continuous phenomenon, we choose to approximate this structure with a discrete two-regimes model. We work in the class of Self-Exciting Threshold AutoRegressive (SETAR) models. Our model writes:

$$Y_t = C^1 + A^1 Y_t + \sum_{k=1}^{P} B_k^1 Y_{t-k} + \left(C^2 + A^2 Y_t + \sum_{k=1}^{P} B_k^2 Y_{t-k} \right) \mathbb{1}_{c_{t-d} \geqslant \gamma} + U_t \tag{1}$$

$$Y_t = [X_t, \; \Delta \ln GDP_t, \; \Delta \ln CPI_t, \; \Delta r_t]\prime \text{ and } t = 1 \ldots T$$

where Y_t contains the quarterly growth rate of the real Gross Domestic Product, of the consumer price index, the first difference of the lending rate on loans to French firms, and alternatively two different measures of credit market conditions (as detailed in Section 2): the first difference of the lending spread between small and large firms, and the volatility of the CAC40 index (henceforth VCAC40).

C^1 and C^2 are constants, A^1 and A^2 reflect the contemporaneous dependencies of Y_t, and B_k^1, B_k^2 are the matrices associated with the k-th lagged values of Y_t. Additionally, U_t are structural disturbances and each U_t^i in $U_t = [U_t^1, U_t^2, U_t^3, U_t^4]\prime$ is taken as independent and identically distributed.

Non-linearities are introduced through the interaction term $\mathbb{1}_{c_{t-d} \geqslant \gamma}$. The measure of credit market conditions c_{t-d} is modelled as a moving average on Y_t, and more specifically here on the credit conditions X_t. The order m of the moving average is unknown and determined exogenously. In addition, we define d as an *unknown* diffusion parameter, and γ as the *unknown* critical threshold value, above which the model will shift to another regime.

This choice of modelling allows us to distinguish between two credit regimes: a first regime of *"standard"* credit conditions when $c_{t-d} < \gamma$ and a second regime of *"stressed"* credit conditions when $c_{t-d} \geqslant \gamma$. As the indicator function will endogenously evolve with Y_t variables, this methodology is appropriate to study the non-linear propagation of shocks in the economy.

Lastly, the introduction of A^1 and A^2 matrices allows for contemporary dependencies between Y_t variables. For this VAR to be estimated, we require an additional *causal ordering*

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assumption. This ordering method, as first introduced by Sims (1990), gives a recursive structure to the VAR model. Our choice of ordering is as follows:

$$X_t \implies \Delta \ln GDP_t \implies \Delta \ln CPI_t \implies \Delta r_t \tag{2}$$

that is, credit conditions only reacts to lagged values of other variables and has no contemporaneous dependency. GDP contemporaneously reacts to credit conditions and with lag to inflation and the interest rate, etc. As a result, our A^1 and A^2 matrices are lower triangular matrices with zeros on the diagonal.

This choice of ordering reflects the timing of decisions and reaction delays in the economy. It is standard in the empirical literature (*cf.* Walsh and Wilcox (1995) [10] or Lown and Morgan (2002) [18]) to place GDP before inflation and the interest rate, in order to replicate the timing of decisions in the economy: economic activity determines the pricing decision, and the central bank (i.e. the interest rate) reacts to inflation. However, we depart here from the usual choice of placing credit conditions as the fourth variable in the VAR, and choose to make it the first variable of our model. This choice is driven by our identification strategy that these credit conditions measures should be relatively independent of the economic cycle. In particular, it embodies the fact that financial markets and banks "moves" first and anticipate on the developments of the economy before the realization of shocks.

Note that this recursive VAR approach is similar to an *ex ante* Cholesky decomposition choosing one of the $n!$ possible orderings.

3.2 Estimation procedure

As mentioned above (γ, d) are unknown parameters and need to be estimated along with the other coefficients. If (γ, d) were known, the estimation of the model would be straightforward, proceeding by Ordinary Least Squares. In our context, we resort to Hansen (1996) estimation method to identify (γ, d).

Denoting $\theta = [C^1, C^2, A^1, A^2, B^1, B^2]$ the set of standard parameters to be estimated, the estimation breaks down as follows:

1. Choose d_{max}, the maximum diffusion lag. Define $D = \{1, \ldots, d_{max}\}$.[9]

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[9] $d = 0$ is excluded to avoid endogeneity issues.

2. Choose N_γ, the number of potential γ we want to test. $\forall n \leq N_\gamma$, denote $c_{(n)}$ the $\frac{n}{N_\gamma}$-th quantile of the empirical sample $\{c_1 \ldots c_T\}$, and define the set of potential γ: $\Gamma = \{c_{(1)}, \ldots, c_{(N_\gamma)}\}$.

3. Conditionally on each $(\gamma, d) \in \mathcal{S} = \Gamma \times D$, the model is estimated by OLS. We obtain estimates for $\hat{\theta}(\gamma, d)$, $\forall (\gamma, d) \in \mathcal{S}$.

4. We choose $(\hat{\gamma}, \hat{d}) = \underset{(\gamma,d)\in\mathcal{S}}{\text{argmin}}\, \text{Cr}(\gamma, d)$, where $\text{Cr}(\gamma, d) = \ln(\det[\text{Var}(\hat{U})])$ is a *log-determinant* selection criterion. Henceforth, this choice will be described as the *optimal* couple.

This approach is a *grid search* approach on a set of possible values for γ and d.[10] Note that the search set for γ is elaborated on the empirical distribution of c_{t-d} refining the grid where c_{t-d} is denser. As explained in Balke (2000) [3], we also exclude the border values so that at least 10% of the observations are in each regime.[11]

Lastly, as there is no *a priori* on the value of P, we determine the VAR order using a classical information criteria on the fully specified TVAR. To take into account the particular estimation methodology, we repeat the algorithm for each possible values of p we want to test (here we allow up to four lags). For each optimal TVAR estimated at a given p, we compute two information criteria (Schwarz information criterion and a bias-corrected Akaike information criterion) and select the minimizing and most parsimonious p one.

3.3 Testing for the presence of non-linearities

As we use a non-linear VAR model, it is important to test for the presence of non-linearities. This is equivalent to test if the TVAR model is preferred to a linear VAR constructed on the same set of data. Formally, we want to test the null hypothesis H_0 against the alternative H_a:

$$H_0 : C^2 = A^2 = B^2 = 0 \text{ against } H_a : C^2 \text{ or } A^2 \text{ or } B^2 \neq 0 \tag{3}$$

However, as (γ, d) is not observed under the null hypothesis, the behaviours of the standard test statistics are non-standard. As a result, we follow the likelihood ratio approach developed in Hansen (1999) [14] to test for the presence of non-linearities in SETAR models.

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[10]This grid search is a discrete evaluation of a Maximum Likelihood program (*cf.* Appendix A).

[11]In other words, we exclude the top and bottom 10-th centiles.

This test statistic is derived from a standard likelihood ratio statistic between an unconstrained TVAR model estimated conditionally on (γ, d), and the linear constrained VAR model (the H_0 model).

$$\mathcal{LR}_{(\gamma,d)} = (T - P) \ln \left(\frac{\det \widehat{\Sigma}|_{\text{linear VAR}}}{\det \widehat{\Sigma}|_{\text{estimated TVAR}}} \right) \text{ giving } \begin{cases} avg - \mathcal{LR} = \underset{(\gamma,d) \in \mathcal{S}}{\text{mean}} \ \mathcal{LR}_{(\gamma,d)} \\ sup - \mathcal{LR} = \underset{(\gamma,d) \in \mathcal{S}}{\sup} \ \mathcal{LR}_{(\gamma,d)} \end{cases} \quad (4)$$

where $\widehat{\Sigma}|_{\mathcal{M}} = \text{Var}(\hat{U})$ is the estimated variance-covariance matrix of the disturbances of model $\mathcal{M}$. From this LR test statistic, we derive two relevant test statistics namely $avg - \mathcal{LR}$ the average likelihood ratio statistic, and $sup - \mathcal{LR}$ the maximum likelihood ratio statistics both computed over the entire search grid.

As mentioned above, the statistics' distributions are here non-standard. We therefore require to simulate this distribution by bootstrapping. We follow Hansen (1999) [14] algorithm described in the Appendix B. Note that this simulation procedure requires the additional assumption that U_t disturbances are independent of past history Ω_{t-1} on Y and are homoskedastic.[12]

3.4 Generalised Impulse Response Functions (GIRFs)

The non-linear framework of our VAR-model does not allow direct computations of Impulse Response Functions. As $\mathbb{1}_{c_{t-d} \geq \gamma}$ is endogenously determined, we compute Generalised Impulse Response Functions (henceforth GIRFs) following Koop, Pesaran and Potter (1996) [16]. Those GIRFs take into account the endogenous structure of the indicator function and the fact that in this particular setting the *symmetry*, *linearity* and *history independence* properties of the standard IRF in the linear setting fail. In other words, the variables' responses are no longer independent of the sign of the shock, its magnitude and the initial conditions.

At date t, the response at horizon k to a shock u_t is computed as the difference between the expected value of Y_{t+k} conditional on past history Ω_{t-1} and the shock u_t minus the value that would prevail in the absence of shock:

$$GIRF_k = \mathbb{E}\left(Y_{t+k}|u_t, \Omega_{t-1}\right) - \mathbb{E}\left(Y_{t+k}|\Omega_{t-1}\right) \quad (5)$$

---

[12]Note that Hansen (1999) shows that this bootstrapping method can be adapted to the case of heteroskedastic errors.

The right-hand side of the equation is computed according to the algorithm described in the Appendix D. These GIRFs are computed by a bootstrapping algorithm described extensively in the Appendix. Response functions are computed conditionally on a given initial credit regime ($\mathbb{1}_{c_{t-d} \geqslant \gamma} = 0$ or $\mathbb{1}_{c_{t-d} \geqslant \gamma} = 1$). Therefore, for each response of an endogenous variable to a shock, we compute two IRFs: one starting in an *unstressed* credit regimes and one starting in a *stressed* regime. Within each subgroup, each term of Equation 5 is evaluated as the mean of responses over all bootstrapped draws and over all possible initial conditions within the chosen subgroup.[13] However even though the initial regime is fixed, these GIRFs allow endogenous switches in the indicator function and take into account the non-linear aspect of our model.

Moreover, these IRFs correct the *history dependence* of our responses in a non-linear framework. In order to account for the *symmetry and linearity dependence* of responses, we draw GIRFs for positive and negative 1- and 2-standard deviation shocks. This allows us to evaluate the sensitivity of the GIRFs with respect to both the magnitude and the sign of the shock.

4 Results

Numerous models, specifications and sample sizes were tested and results presented in this Section are the selection of the most stable models in terms of estimation and Impulse Response Functions. The next Section details the selection process of these models.

4.1 Identification of non-linearities and constraint periods

Estimation results   Estimation results are presented in Table 1.

Due to the large number of parameters to estimate, the information criteria select VAR models built with only one lag. Transmission delays d range from d = 2 to 3 quarters, implying that the real economy takes the credit environment into account at a relatively moderate pace. For our two models, the existence of an accelerator effect is given by the test statistics. Model A, based on the CAC40 volatility, argues for the absence of non-linearities in the propagation of shocks to the economy, and the relationship between credit and activity is, in this respect, linear. On the contrary, model B, based on the lending spread between small and large firms, pleads in favour of a financial accelerator effect, as three out of four tests reject

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[13]See the detailed algorithm in the Appendix D for further explanations.

Table 1: Results for threshold-VAR

Model	Credit stress measure	Estimated threshold	Avg-LR	Sup-LR	Avg-Wald	Sup-Wald	% of observations in standard credit regime on 2000-2013
A	CAC40 volatility		35.17	57.32	32.49	54.48	
	m=3, P=1, d=2	γ = 0.0384	(0.16)	(0.17)	(0.07)*	(0.13)	50.9%
B	ΔLending rate spread		36.83	70.83	34.20	69.10	
	m=5, P=1, d=3	γ = -0.0200	(0.12)	(0.02)**	(0.03)**	(0.01)***	63.6%

System includes: the chosen credit stress measure, GDP growth, CPI inflation and the first difference of the lending interest rate on credits of more than two years to NFCs.

The lending rate spread (in first differences) model is estimated on (1984Q3-2013Q4), and the CAC40 volatility (in levels) model on (1987Q3-2013Q4).

Results are from *optimal* models with VAR order P, a diffusion delay d, and a moving average of order m.

Statistics *Avg-LR* and *Sup-LR* (resp. *Avg-Wald* and *Sup-Wald*) correspond to the average and the maximum of the likelihood ratio (resp. Wald) statistics on the search grid. p-values are shown in parentheses. *** represents a rejection of the null hypothesis at a 1% level of confidence, ** at a 5% level and * at a 10% level.

the null hypothesis at the 5% level of confidence.
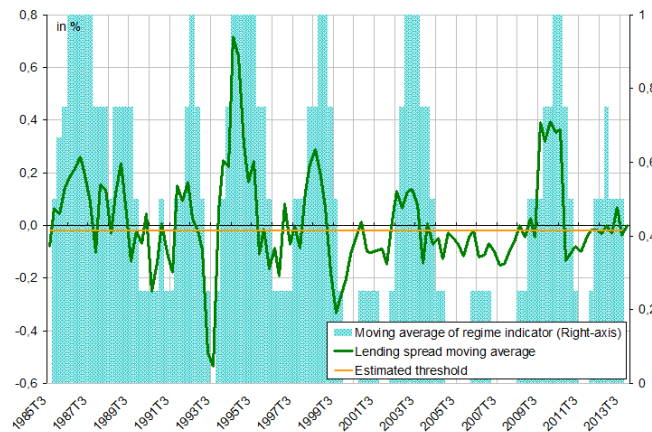
Figure 11: First difference of the lending spread moving average and estimated threshold (including the transmission delay $d = 3$)

We now turn to a more specific study of non-linearities in model B. With respect to model A, as the existence of non-linearities is rejected, no differentiated credit regimes are identified.

Credit constraint periods in model B: *flight to quality*   The corresponding moving average of the lending spread (in first differences) is plotted against its estimated threshold in Figure 11. We represent a four quarters moving average of the dummy indicator $I_{c_{t-d} \geqslant \gamma}$.[14] Note that we plot the d-lagged moving average, that is c_{t-d}, so that the sudden increase of the lending spread starts in 2009Q3, whereas it starts three quarters earlier (2008Q4) in the data. This allows to directly identify periods of stress on this graph as dates where the moving average crosses the threshold.

Figure 11 allows to identify three main periods of credit restriction (namely here *flight to quality* phenomenons) since 2000 (2002Q3-2004Q3, 2009Q1-2011Q1 and 2012Q2-2013Q3). Indeed, the 2008 great recession is clearly identified on the moving average. This reflects a faster transmission of the decreasing main refinancing rate at the ECB for large firms. This differentiated transmission directly relates to the *flight to quality* theory, where, in uncertain periods, banks turn more easily to large firms considered are sounder and less sensitive to future adverse shocks. Moreover, and as previously stated (see Figure 4), firms (and most probably large firms) massively turned in 2008 towards the bond market. In order to limit the contraction of their client base, banks may have lowered lending rates to large firms to fight this substitution. Identically, the observed increase in the lending spread in 2002/2004 corresponds to a faster transmission of the decreasing refinancing rate at the ECB to large firms. The last 2012-2013 period corresponds to the developments of the sovereign debt crisis that hit the Eurozone in the aftermath of the Great Recession.

These periods do indeed correspond to observed credit contraction periods, and are reassuring as to the relevance of the indicator used. Strictly speaking, this coherence does not provide conclusive evidence of a causal relation between credit contractions and recessions.

Before 2000, the model clearly identifies the 1992/1993 French recession but also other episodes of credit stress. The identification of these periods comes from the higher average observed value and volatility of the lending spread before the creation of the monetary union (*cf.* Figure 12). As a result, it reflects less developed credit markets with higher lending rates,

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[14]This choice of moving average representation is made to ease identification of stress periods as the gross indicator is highly volatile. This volatility is both a result of a binary modelling for the switch between regimes, which qualifies as a credit stress values which can be both only slightly higher than the threshold or much higher (like those observed at the end of 2008), and of the choice of a lending spread in first differences rather than in level.
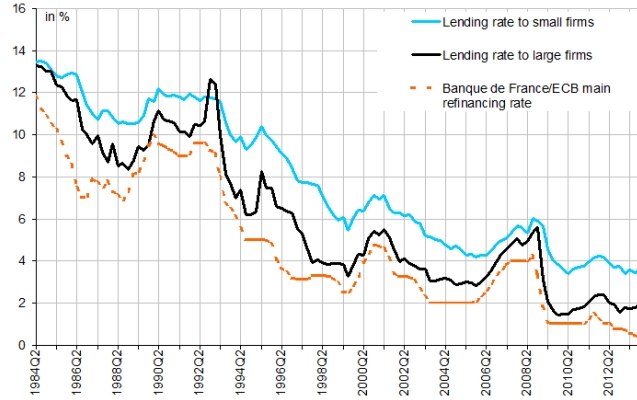
Figure 12: Disaggregated lending rates on loans of less than two years for small and large firms

and *de facto* a higher probability for the lending spread to stand above the estimated threshold.

In all, in model B, the French economy experienced 20 quarters of tighter lending conditions over the 2000-2013 period. This time span is larger than the actual time in recession, which is 16 quarters according to the CEPR European cycle dating, and 7 quarters of recession in France with the restrictive criterion (*cf.* Table 2).

Table 2: Business cycles dating

Euro Area (CEPR)	France (RC)
1974Q3-1975Q1	1974Q4-1975Q2
1980Q1-1982Q3	1992Q2-1993Q1
1992Q1-1993Q3	2008Q2-2009Q2
2008Q1-2009Q2	2012Q4-2013Q1
2011Q3-	

CEPR business cycle dating for the Euro area as a whole. The methodology is similar to the NBER business cycle dating committee and can be found on this website.

RC corresponds to the restrictive (and debatable) recession criterion of two consecutive quarters of negative GDP growth.

4.2 Impulse Response Functions

In this section, an increase in the credit stress variable translates into a more binding constraint as an increase in the volatility of the CAC40 index, or an increase in the lending spread between small and large firms, reflects a deteriorated credit environment. Impulse Response

Functions for model A are linear VAR impulse response functions (Figure 13), whereas model B response functions are generalized IRFs for non-linear VAR (Figure 14) as exposed in Section 3.4. The full set of impulse responses functions is presented on Figures 18 to 25 in the Appendix G and H, and usual economic mechanisms, such as an increase of interest rates and a deterioration of credit conditions following a shock of inflation therefore resulting in a fall in GDP growth, are clearly identified. For the purpose of our analysis, we only focus in this section on the link between activity and credit conditions, and only refer to GDP impulse responses to the different shocks.

(a) Shock of GDP

(b) Shock of inflation

(c) Shock of interest rate

(d) Shock of VCAC40
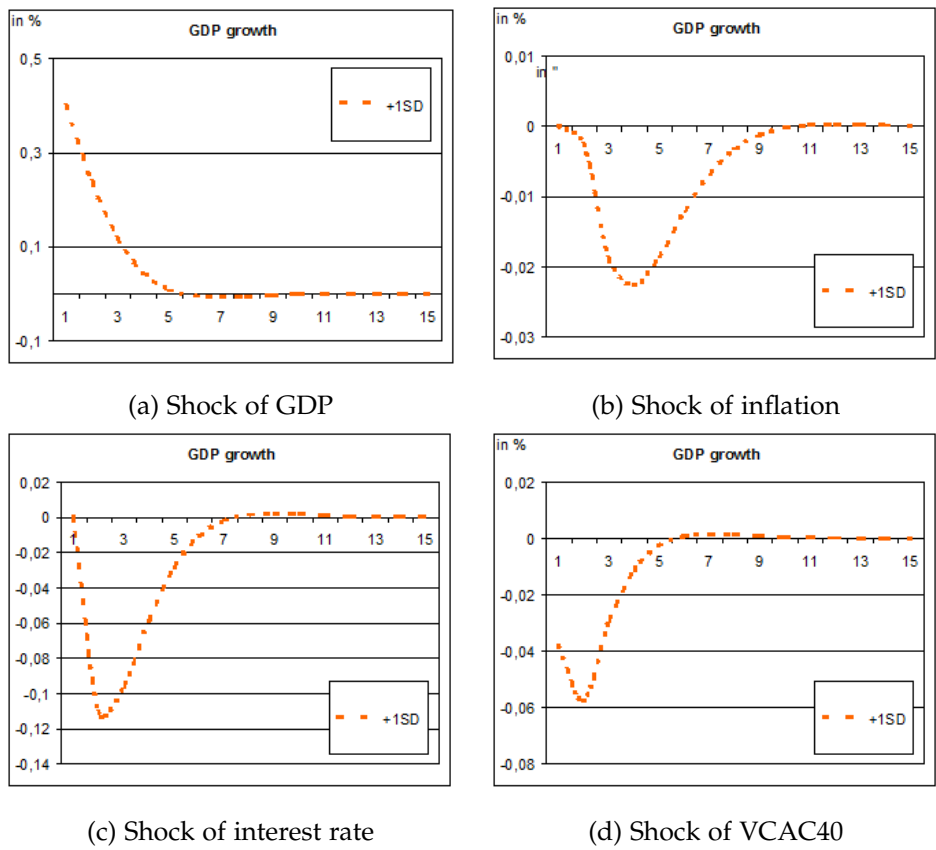
Figure 13: Impulse Responses of GDP growth to one standard deviation shock in model A

Responses of GDP growth For model A estimated on the volatility of the CAC40 index, since the tests plead against the existence of a non-linear financial accelerator effect, only linear impulse response functions are computed (*cf.* Figure 13). They present profiles that are consistent with economic theory. Following a +1-standard-deviation shock of inflation, inter-
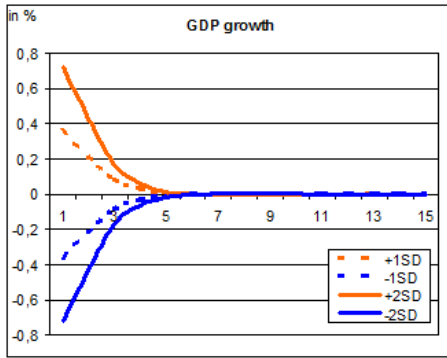
(a) Shock of GDP - Initial *standard* regime
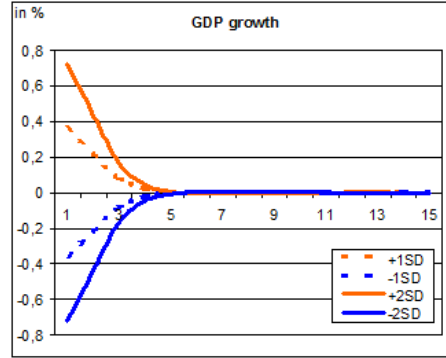
(b) Shock of GDP - Initial *stressed* regime
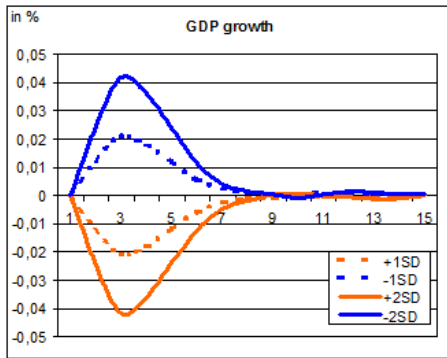
(c) Shock of inflation - Initial *standard* regime
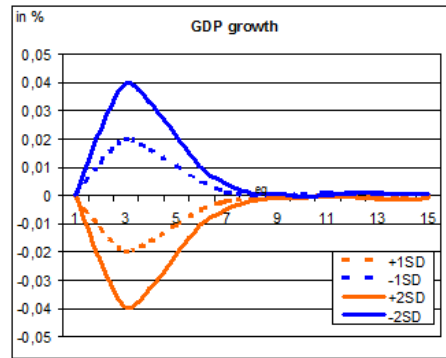
(d) Shock of inflation - Initial *stressed* regime
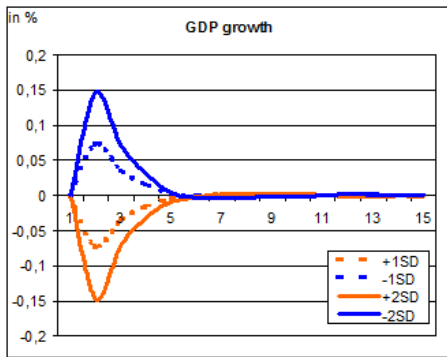
(e) Shock of interest rate - Initial *standard* regime
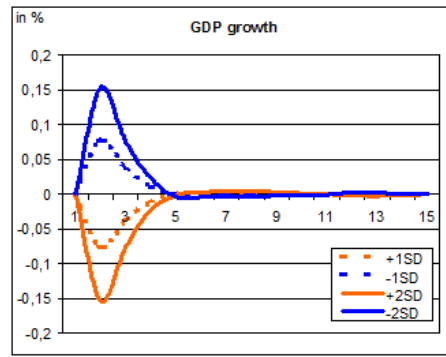
(f) Shock of interest rate - Initial *stressed* regime
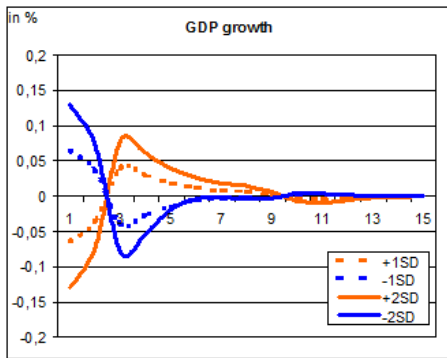
(g) Shock of lending spread - Initial *standard* regime
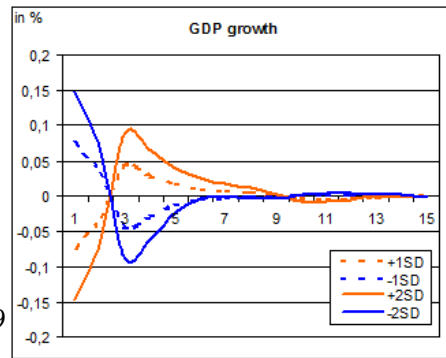
(h) Shock of lending spread - Initial *stressed* regime

29

Figure 14: Impulse Responses of GDP growth to one or two standard deviations shock in model B

est rate or credit conditions, GDP growth decreases starting from the second quarter. This delay or absence of reaction during the first quarter directly results from our ordering and structuring hypothesis. Convergence is achieved after one to two years.

These results are a useful benchmark to analyse the results of model B's generalized impulse responses. In particular, persistence is of similar order in the responses plotted in Figure 14. With respect to the amplitude of shocks, interest rate shocks have a stronger impact on GDP growth (in absolute value) in model A (with a maximum deviation of -0.11% of GDP growth in model A against -0.07% in model B for a one standard deviation shock).

Taking a closer look at the existence of asymmetries in impulse responses of model B (see Figure 14), a striking feature is the quasi absence of differences across initial credit regimes, in contradiction with the results of the tests. This lack of asymmetry between initial regimes results from the estimation of a threshold separating our sample in two halves of relatively similar sizes. Figure 11 shows that an important number of observations stands around the estimated threshold. As a result, even for small shocks, a switch in credit regimes can occur and the persistence of the model in one regime is low. Generalized IRFs being computed and averaged on all possible initial conditions (conditional on an initial credit regime), this similarity between initial conditions for both regimes results in quasi identical responses for both initial credit regimes. This is corroborated by Figure 17 in the Appendix C, with a probability of being in the *stressed* credit regime in the absence of shocks (green curve) stable and close to 50%.

As a result, asymmetries are absent of our GIRFs.[15] The GIRFs dependence to the sign and the magnitude of shocks is similar to a linear model. A negative two standard deviations shock will be opposite and twice stronger as a positive one standard deviation shock.

In the end, results for both models contrast with Balke (2000) [3] on United States data, identifying clear asymmetries in the response of the economy across credit regimes. Calza and Sousa (2006) [9] replicating the same analysis at the European aggregate level also find a weaker importance of non-linearities for macroeconomic responses. In light of results concluding to the absence of non-linearities in France, this might suggest that Calza and Sousa

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[15]One exception is the response of the lending spread to a shock of GDP growth (*cf.* Figure 22) or interest rate (*cf.* Figure 24).

non-linearities may have been driven by countries with different banking structures.

4.3 Contribution analysis
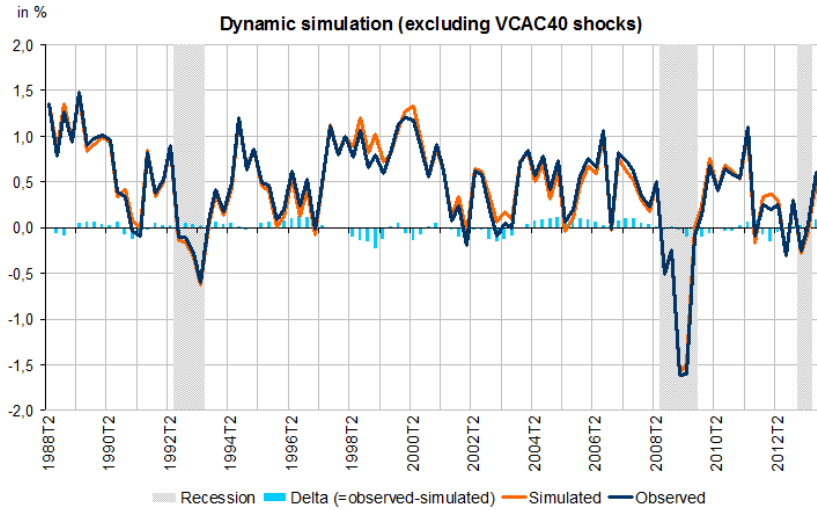
(a) Model A
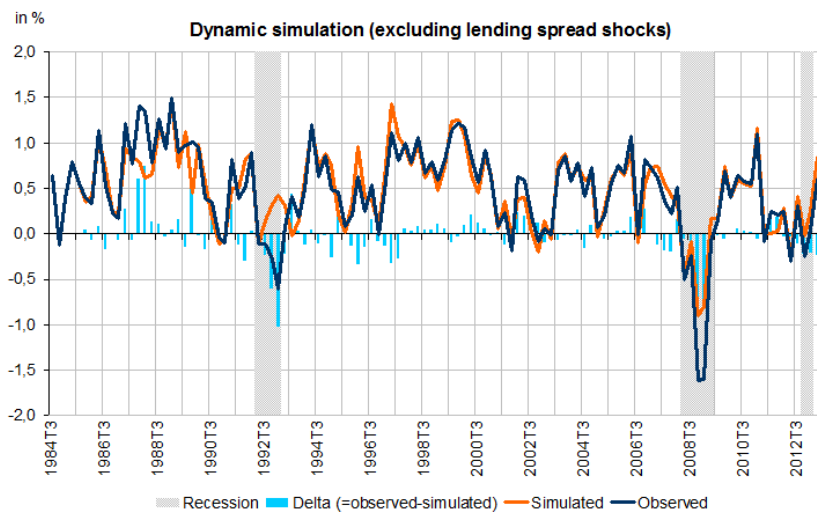
(b) Model B

Figure 15: Dynamic simulation in the absence of credit conditions shocks

A last analysis is conducted on our models in order to evaluate the cost of credit conditions fluctuations for the economy. Pragmatically, the underlying issue of this paper is to assess the cost of credit shocks during the 2008 crisis, but also other major financial crises as
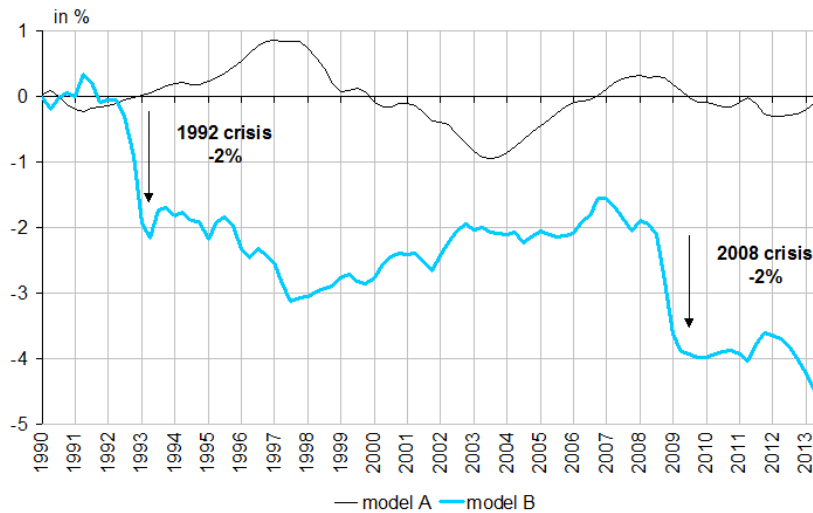
Figure 16: Dynamic simulation in the absence of credit conditions shocks: cumulated impact of credit stresses on GDP growth since 1990

the sovereign debt crisis. Answering this question is usually conducted using an historical decomposition of contributions to GDP growth of the different shocks.

To identify these contributions, we compute the dynamic simulation of the model (linear for model A and non-linear for model B) in the presence of all observed shocks except the credit conditions ones. We therefore depart from the methodology presented in Balke (2000) [3], and a justification of this choice is presented in the Appendix E.

The first advantage of our method is its applicability for both type of linear and non-linear models, therefore allowing for a coherent framework to compare both models. A second advantage is the ability to compute a lower bound to the effect of only credit conditions shocks in the economy. The estimated contributions are indeed a lower bound as it does not take into account second turn effects potentially magnifying the cost of credit conditions, that is the effect of other shocks on credit conditions and therefore on credit switches.

The results of those simulations are plotted on Figure 15. Recession identified by the restrictive criterion of two consecutive quarters of negative growth are identified by the grey shaded areas.

The first important feature of these contribution graphs is the differentiated importance of credit conditions shocks in both models. In the linear model A estimated on the volatility of the CAC40 index, credit conditions play only a minor role and account on average only for 0.06% of GDP growth (in absolute value). On the contrary, in model B identified as non-linear, switching credit regimes plays a more important role during the 1992 and 2008 crises, accounting for 0.15% of GDP growth (in absolute value). The fact that model A displays a weaker contribution of credit condition shocks as compared to model B could follow from the fact that the interest rate lending spread is a better proxy of credit behaviours than the volatility of the CAC40 index, and therefore displays a stronger link with GDP growth.

Surprisingly, credit conditions seem not to have a negative impact in France on GDP growth during the 2011/2012 sovereign debt crises in the Eurozone. However in model B, the cumulated cost of credit conditions fluctuations[16] (*cf.* Figure 16) averages 2 p.p. of GDP growth over the 2008Q1-2011Q1 period (against 0.5 p.p. in model A). On a longer period in model B, we observe that the cost of *flight to quality* for the 1992 crisis was close to 2008. Its impact was a permanent and stable one-off shock to GDP.

Moreover, in model A, the plotted cumulated cost of credit conditions is highly cyclical and do not provide with clear information, as opposed to the behaviour in model B. This can be related to the fact that model A was deemed linear whereas model B was constructed as a non-linear TVAR.

Contrary to GIRFs that are independent to initial conditions and therefore non-differentiated across regimes in our model B, these contributions are history dependant and allow to exhibit credit regimes switches, and therefore allow for a more historically oriented analysis. One should not mistake the seemingly strong impact of financial markets on economic activity during the 2008 crisis and the existence of a global financial acceleration phenomenon over the entire period.

Whereas, based on the econometric study and the impulse responses, financial accelerating effects do not dominate in France when studied from a broad time perspective, the particular chronology of adverse shocks in 2008 and onwards did induce non-negligible credit regime switches, further depressing economic activity.

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[16]The cost is measured by the cumulated difference between the observed and the simulated GDP growth series (blue bars on Figure 15).

5 Discussion and robustness

Different hypotheses and choices are necessary for the estimation, and the identification process. Those choices therefore needs to be properly assessed and tested for. Therefore, this section discusses the robustness of the previous results along different lines: (*i*) we test for the proper specification of the model with respect to the stationarity of the variables and the whiteness of residuals, (*ii*) we test the choice of the structural ordering, and (*iii*) we discuss the choice of the dataset.

5.1 Specification of the model

In order to assess the proper specification of our model, we test for the different underlying hypotheses of our estimation methodology: the stationarity of the endogenous variables, and the whiteness of the residuals. Results are presented in Tables 3 to 4.

Table 3 indicates that the stationarity hypothesis is verified for the four variables. Only inflation might be considered slightly non-stationary before 1995 and the creation of the EMU.[17]

With respect to the whiteness of the residuals (*cf.* Table 4), all tests support the hypothesis of white noise residuals, except in model B with a number of lag lower than 4. However, the literature emphasizes the need to test for a large number of lags to increase the power of the test (usually a multiple of the periodicity of the series, here 4).

In all, those results argue in favour of well-specified models.

5.2 Alternative ordering

In a second step and as presented in Section 3, our identification strategy relies on the choice of an *ex ante* ordering, that is a choice of contemporaneous dependences between the different variables. As a reminder, models A and B rely on the following assumption:

$$X_t \Longrightarrow \Delta \ln GDP_t \Longrightarrow \Delta \ln CPI_t \Longrightarrow \Delta r_t \tag{6}$$

This choice reflects the speed of adjustment of banks and financial markets to shocks. However, this choice is non-standard in the literature, Balke (2000) [3] choosing to put credit

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[17]However, this does not hinder our short-term IRFs results as Phillips (1995) [19] shows that impulse responses computed from unrestricted VAR with near-unit roots (which is a more extreme situation than ours) have only inconsistent long-term responses.

Table 3: Stationarity tests

| | KPSS | | | | ERS | | | | Phillips-Perron | | | |
| | Before 2008 | | Full sample | | Before 2008 | | Full sample | | Before 2008 | | Full sample | |
		p-val		p-val		p-val		p-val		p-val		p-val
GDP growth	0,08	S	0,36	S	-4,9	<0.01	-5,6	<0.01	-13,8	<0.01	-25,1	<0.01
Inflation	0,72	NS	0,82	NS	-7,4	<0.01	-8,7	<0.01	-8,0	0.05	-12,1	0.01
Interest rate (in level)	1,06	NS	1,29	NS	-2,7	0.01	-3,3	<0.01	-1,4	0.41	-1,9	0,34
... (first differences)	0,16	S	0,10	S	-5,5	<0.01	-6,1	<0.01	-84,0	<0.01	-94,3	<0.01
VCAC40	0,16	S	0,07	S	-5,3	<0.01	-5,8	<0.01	-13,7	<0.01	-17,6	<0.01
Lending spread (in level)	0,25	S	0,18	S	-4,5	<0.01	-5,2	<0.01	-2,4	0,29	-2,7	0,26
... (in first differences)	0,20	S	0,10	S	-6,4	<0.01	-7,4	<0.01	-85,1	<0.01	-133,3	<0.01

Full sample test were conducted on the full series of residuals, whereas *Before 2008* were conducted on series ending in 2008Q1 to avoid the crisis period non stationary bias.

The null hypothesis tested by the KPSS test is one of stationary series, whereas the Phillips-Perron and Elliot-Rothenberg-Stock tests test for the presence of a unit root.

For the KPSS test, S indicates that the null hypothesis of stationarity is accepted and NS its rejection at the 10% level.

Table 4: Multivariate Ljung-Box test for whiteness of the residuals

| lags | Model A | | Model B | |
		p-value		p-value
4	69,5	0,30	92,2	0,01
6	103,8	0,27	113,3	0,11
8	142,4	0,18	146,4	0,13
10	174,9	0,20	177,0	0,17
12	213,8	0,13	207,6	0,21

The null hypothesis tested by the Ljung-Box test is one of *white* residuals.

conditions in the last position, and Calza and Sousa (2006) [9] as the third variable.

With four variables, there is exactly 4! = 24 possible orderings. As a result, we choose to only focus on Balke's choice of ordering ($\Delta \ln GDP_t \implies \Delta \ln CPI_t \implies \Delta r_t \implies X_t$) as a benchmark case. Other choices of orderings for GDP growth, inflation and interest rates are not discussed here, as it is a common choice in the literature: prices are determined based on observed GDP growth and the interest rate adjusts in response to inflation. Estimation results following this alternative choice are presented in Table 5.

Table 5: Results for T-VAR with alternative ordering

Model	Credit stress measure	Estimated threshold	Avg-LR	Sup-LR	Avg-Wald	Sup-Wald	% of observations in standard credit regime on 2000-2013
A(bis)	CAC40 volatility		35.22	56.13	32.73	53.69	
	m=3, P=1, d=2	$\gamma = 0.0384$	(0.14)	(0.17)	(0.08)*	(0.16)	50.9%
B(bis)	ΔLending rate spread		36.28	68.39	33.71	67.05	
	m=5, P=1, d=3	$\gamma = -0.0200$	(0.08)*	(0.05)**	(0.04)**	(0.02)**	63.6%

System includes: the chosen credit stress measure, GDP growth, CPI inflation and the first difference of the lending interest rate on credits of more than two years to NFCs.

The lending rate spread (in first difference) model is estimated on (1984Q3-2013Q4), and the CAC40 volatility (in level) model on (1987Q3-2013Q4).

Results are from *optimal* models with VAR order P, a diffusion delay d, and a moving average of order m.

Statistics *Avg-LR* and *Sup-LR* (resp. *Avg-Wald* and *Sup-Wald*) correspond to the average and the maximum of the likelihood ratio (resp. Wald) statistics on the search grid. p-values are shown in parentheses. *** represents a rejection of the null hypothesis at a 1% level of confidence, ** at a 5% level and * at a 10% level.

Comparing with results in Table 1 shows identical estimated thresholds, VAR lags and transmission delays. Moreover, non-linearity test results lead to the same conclusion for model A(bis), where non-linearities are rejected, and model B, accepting the hypothesis of a non-linear threshold model. Therefore, it appears that results are relatively robust to the choice of a different ordering of the variables along those dimensions.

However, plotting impulse responses functions for this alternative ordering comforts us in the choice of our ordering. Actually, although estimation results seem comparable, coefficients estimated with the alternative ordering lead to unstable impulse response functions in the

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sense of responses opposite to economic intuition.[18] This instability of Impulse Response Functions is a recurrent feature across specifications and datasets as explained in the next paragraph.

5.3 Dataset and credit conditions indicators

Although the previous stationarity tests show that the lending rate spread in first differences is indeed stationary, its level was also a (stationary) option. The decision to work with a differentiated lending rate spread comes from two reasons. First, levels and first differences do not convey similar information. Working with a differentiated spread allows to capture the dynamic in lending behaviours and to identify sudden changes across periods. However, this choice comes at a price, as it also increases the volatility of our credit stress indicator. Second, the choice of a first differenced indicator was also kept to ensure the stability of the IRFs. Actually, this choice allowed us to derive responses conform to economic intuition.

From a broader prospect, this choice highlights a more general statement of the difficulty to *properly* model financial - real spheres interactions in a linear or non-linear VAR. Therefore, due to these difficulties to obtain a *well behaved* model, a systematic robustness check was conducted to assess the sensitivity of the results to changes in the model.

First and to clarify our intention, the following (exact or fuzzy) criteria are taken to describe what we define as a *well-behaved* model:

- In the first step, the discrimination between a linear and a non-linear model is based on the following parameters:
  - the (formal) likelihood ratio and Wald test statistics

- In a second step, the general *proper* behaviour of the model is assessed with respect to:
  - the conformity of IRFs to economic intuition and mechanisms
  - the viability of the estimated coefficients
  - and if deemed non-linear,
    * the % of time in a constrained regime expected to be coherent with *ex ante* expectations[19]

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[18]In particular, in Model B(bis), we observe a systematic increase in GDP following an increase in the lending spread, that is following a deterioration of credit conditions.

[19]For instance, not more than 50%.

∗ a reasonable diffusion delay parameter d

As mentioned, we conduct a systematic robustness check and estimate variations of our models along the following lines:

1. **Length of the moving average** We allow for a moving average $m = 1 \ldots 6$ quarters. This choice of parameter is key for the characterization of credit constraints periods by the model, as it influences the volatility of the underlying credit constraint indicator.

2. **Different estimation periods** in order to correct for the non-stationarity of the inflation rate at the beginning of the sample that might potentially bias the relationship between inflation and the interest rate.

3. **Choice of variables**

   - Inflation: CPI inflation or GDP deflator growth rate.

   - Interest rates: 3-month Euribor, French sovereign bond rates, or the lending rate to NFCs for loans up/less than 2 years.

   - Lending interest rate spread between small and large firms: whether with a same maturity (less than 15000 euros versus more than 1.5 million euros for less than 2 years) or with crossed maturities[20] (less than 15000 euros for more than 2 years versus more than 1.5 million euros for less than 2 years).

4. **Transformation applied to the variables:** the choice of transformation was mainly driven by the stationarity properties of each series. However, a variable in level or first differences conveys a very different information. In particular for credit stress indicators, an indicator in level measures the level of stress and its persistence at a given date with respect to the entire sample, whereas the same variable in first difference mainly conveys an information on changing behaviours from date to date. An other criterion for the choice of transformations is the "accounting" homogeneity between variables (stock or flow) or economic homogeneity (for instance, the traditional Taylor rule implies that the level of the interest rate is homogeneous with the level of inflation). In the end, we retain the following alternatives:

   - Inflation in level or first difference

   - Nominal or real interest rates, in level or first difference

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[20]The idea behind this choice is to take into account both the facts that mainly small firms borrow small amounts with long maturities, and that only large firms are able to borrow large amounts with short maturities.

- Lending spreads in level or first difference

5. **Choice of ordering**: We allow for an alternative choice of ordering as presented in the previous subsection.

In all, the systematic estimation of those different variations of our model highlights the difficulty to construct a *well-behaved* model taking into account the effect of financial variables over the real economy in the case of France.

Indeed, the models presented in Section 4 are models selected among the full set of estimated models for their properties. Other models were rejected as they do not fulfil the set of conditions imposed above. In particular, a recurring result is the difficulty to obtain proper impulse response functions of GDP to credit stress shocks, both in linear or non-linear VAR models. In most cases, a deterioration of the credit environment leads to a counter-intuitive increase in the growth rate of GDP.

These compelling results may reflect three different explanations:

1. The absence of financial phenomenon in France over the considered period, so that we are indeed incapable to capture them. The weak evidence presented in our models corroborate this possibility. However, the important developments of financial markets in France over the last two decades question this statement.

2. The inadequacy of VAR and TVAR models to capture the transmission of financial shocks to the real economy. However, the identification of non-linearities in the United States by Balke (2000) [3] and in the European union by Calza and Sousa (2006) [9] with the same methodology tends to oppose this view.

3. The inadequacy of our credit stress variables to describe the financial mechanisms at work in France. Again, as we construct our credit indicators close to the ones used by Balke (2000), this reason seems weak. However, this could also mean that financial mechanisms as identified by the lending interest rate spread and the volatility of the CAC40 are not relevant for France, and that other financial phenomenons may be at work.

Note that a previous version of this paper (see Alhenc-Gelas et al. (2014) [1]) develops the same methodology on monthly series using four different credit indicators: namely, the VSTOXX50 index, a bank lending spread between small and large firms, the difference in

the growth rate of new loans between small and large firms and the bank margin spread on new loans with respect to the EURIBOR 3 months from 2000 to 2013. They arrive to similar conclusions: on monthly data, three out of four models identify non-linearities based on the tests but do not exhibit significant differentiated responses across regimes. As such, this is in line with evidence provided here of the weak role of financial acceleration in France.

6 Conclusion

Using French aggregate data over the period 1987-2013, we assess the importance of financial accelerator phenomenons and the cost of credit conditions during the recent crises. Replicating the threshold-VAR methodology of Balke (2000) [3] for a large number of potential models, the use of Generalized Impulse Responses and a new yet simple contribution analysis over the recent periods allows to give a few insights on financial-real economy interactions in France.

The formal test identification of the existence of non-linearities contrasts with the absence of differentiated responses across regimes in the impulse responses functions, and cast doubts on the importance of financial acceleration in the link between credit and activity in France when considered over the entire period. However, even though Kremp and Sevestre (2012) [17] or Cabannes et al. (2013) [8] argue in favour of an absence of credit constraints in France during the 2008 crises at the microeconomic (partial equilibrium) level, we estimate that the macroeconomic (general equilibrium) impact of deteriorated financial conditions might have been responsible since 2008 for a cumulated loss of 0.5% due to *financial markets stresses* or 2% of GDP growth due to *flight to quality*.

These results seem in line with those of Calza and Sousa (2006) [9] identifying a minor influence of non-linearities arising from European credit market imperfections on activity. Focusing here on France, we show the absence of strong non-linearities and financial acceleration effects. However, conclusions are fragile and we perform a detailed robustness analysis with respect to the specification of the model.

Using different input datasets, we stress that across all model specifications (with changes in the input variables, their transformation, etc.) obtaining a *well-behaved* model, both in terms of econometric and economic properties (that is well-specified and economically valid) is a difficult task. Results presented in this paper correspond to the specific selection of such *well-behaved* models. This estimation difficulty might reflect either the inadequacy of VAR

and TVAR for capturing the impact of financial shocks on the real economy. A more likely hypothesis is that the financial transmission channels at work are different in France than those captured by our indicators and that further research needs to be conducted.

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Appendix A   Maximum Likelihood Estimation equivalence and LR testing

Non-linear VAR models are usually estimated by Maximum Likelihood Estimation, therefore requiring an additional assumption on the distribution of the residuals. In our model, if we assume Gaussian disturbances, the likelihood of Y_t conditionally on $Y_{t-1}, Y_{t-2}, \dots$ writes:

$$f(Y_t | Y_{t-1}, Y_{t-2}, \dots) = \frac{1}{(2\pi)^{\frac{N}{2}} |\text{Var}(U)|^{\frac{1}{2}}} \exp^{-\frac{1}{2} U_t' \text{Var}(U)^{-1} U_t} \tag{7}$$

where $N = 4$ is the length of Y_t, and U_t are the structural disturbances in Equation 1. In addition, if we assume independence, the sample log-likelihood writes[21]

$$\ln \mathcal{L}_t(\theta, \gamma, d) = \frac{1}{T-p} \sum_{t=p+1}^{T} \ln f(Y_t | Y_{t-1}, Y_{t-2}, \dots)$$

$$= -\frac{N}{2} \ln 2\pi - \frac{1}{2} \ln |\widehat{\text{Var}}(\hat{U})| - \frac{1}{2(T-p)} \sum_{t=p+1}^{T} \hat{U}_t' \widehat{\text{Var}}(\hat{U})^{-1} \hat{U}_t \tag{8}$$

$$= -\frac{N}{2} \ln 2\pi - \frac{1}{2} \ln |\widehat{\text{Var}}(\hat{U})| + \text{constant}$$

$$\text{since } \widehat{\text{Var}}(\hat{U}) = \frac{1}{T-p} \sum_{t=p+1}^{T} \hat{U}_t \hat{U}_t' \tag{9}$$

In the end, the Maximum Likelihood Estimator is $(\hat{\theta}, \hat{\gamma}, \hat{d}) = \underset{(\theta, \gamma, d)}{\arg\min} \frac{1}{2} \ln \text{Var}(\hat{U})$, which corresponds to the log-determinant criterion described above. Hence, the *grid search* approach used in this paper is a discrete equivalent of a Maximum Likelihood Estimation with Gaussian residuals.

This likelihood maximisation approach is also fully compatible for Likelihood Ratio testing. Indeed, for a given couple (γ, d), the test statistics is given by Equation 4. If (γ, d) is known, it follows a standard $\chi^2(k)$ distribution with k being the number of parameters constrained in the null hypothesis.[22]

Moreover, as $\mathcal{LR}_{(\gamma, d)}$ is a decreasing function of $\det \hat{\Sigma}|_{\text{estimated TVAR}}$, the choice of (γ, d) as minimising $\det \hat{\Sigma}|_{\text{estimated TVAR}}$ also implies the maximisation of $\mathcal{LR}_{(\gamma, d)}$. As a result, the final test statistic is intuitively close to the maximisation over $d_{max} N_\gamma$ distinct asymptotic χ^2 random variables (ie. the $\mathcal{LR}_{(\gamma, d)}$), and is fully coherent with the (γ, d)-selection criterion.

Note that this final distribution will be "greater" than the standard $\chi^2(k)$. Therefore, it we do not reject H_0 using a $\chi^2(k)$, we would not reject using the true distribution.

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[21]As $\widehat{\text{Var}}(\hat{U})$ is a variance-covariance matrix, it is symmetric definite positive and can be diagonalized.

[22]Here, we have $k = 4 + 6 + 16p$.

In addition, Andrews and Ploberger (1994)[2] show the two $avg - \mathcal{LR}$ and $sup - \mathcal{LR}$ statistics are the limit cases of a more general form of *average exponential* test statistics.[23] Whereas $avg - \mathcal{LR}$ is designed for alternatives H_a close to H_0, $sup - \mathcal{LR}$ is suitable for alternatives far from the null hypothesis.

Appendix B   Test statistics distribution: bootstrapping algorithm

As explained in Section 3, in our TVAR framework, usual test statistics are non-standard. Therefore, the distributions need to be simulated. We follow Hansen (1999) algorithm.

1. Generate a random shock sample $\{\hat{\varepsilon}_k\}_{k=1...T-p}$ from the estimated residuals of the linear VAR model.

2. Recursively generate a bootstrapped sample $\{Y^*\}_{k=p+1...T}$ with the estimated *linear* model using: the *fixed* initial conditions $\{Y_1, Y_2, \ldots, Y_p\}$ and the sequence of random shocks $\{\hat{\varepsilon}_k\}_{k=1...T-p}$.

3. Compute the two $\mathcal{LR}^*$ statistics on this simulated sample.

4. Repeat Steps 1 to 3 a large number of times ($N = 500$) and finally determine p-values as the percentage of simulated test statistics $\mathcal{LR}^*$ that are greater than the true $\mathcal{LR}$.

Appendix C   Evolution of the probability to be in the *stressed* credit regime

An other tool for studying switches between credit regimes in model B is the Impulse Response Function of the indicator function $I_{c_{t-d} \geq \gamma}$, that is the evolution of the probability to be in the *stressed* credit regime. As for GIRFs, responses are computed following Koop, Pesaran and Potter [16] methodology and are conditional on an initial credit regime. However, as mentioned in previous section, responses are very similar across regimes and we choose to

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[23]*Average exponential* test statistics take the form: $exp - \mathcal{LR} = (1 + c)^{-\frac{p}{2}} \iint \exp\{\frac{1}{2}\frac{c}{1+c}\mathcal{LR}_{(\gamma,d)}dJ_1(\gamma)dJ_2(d)\}$ where p is the number of parameters being tested in the null hypothesis, c is a constant and J_1 and J_2 are weight functions over γ and d. The $avg - \mathcal{LR}$ and the $sup - \mathcal{LR}$ are respectively obtained after renormalisation, for $c \to 0$ and for $c \to \infty$. In the case of a grid search, J_1 and J_2 are discrete functions uniformly distributing weights over all tested values of γ and d.

(a) Shock of GDP

(b) Shock of inflation

(c) Shock of interest rate

(d) Shock of lending spread
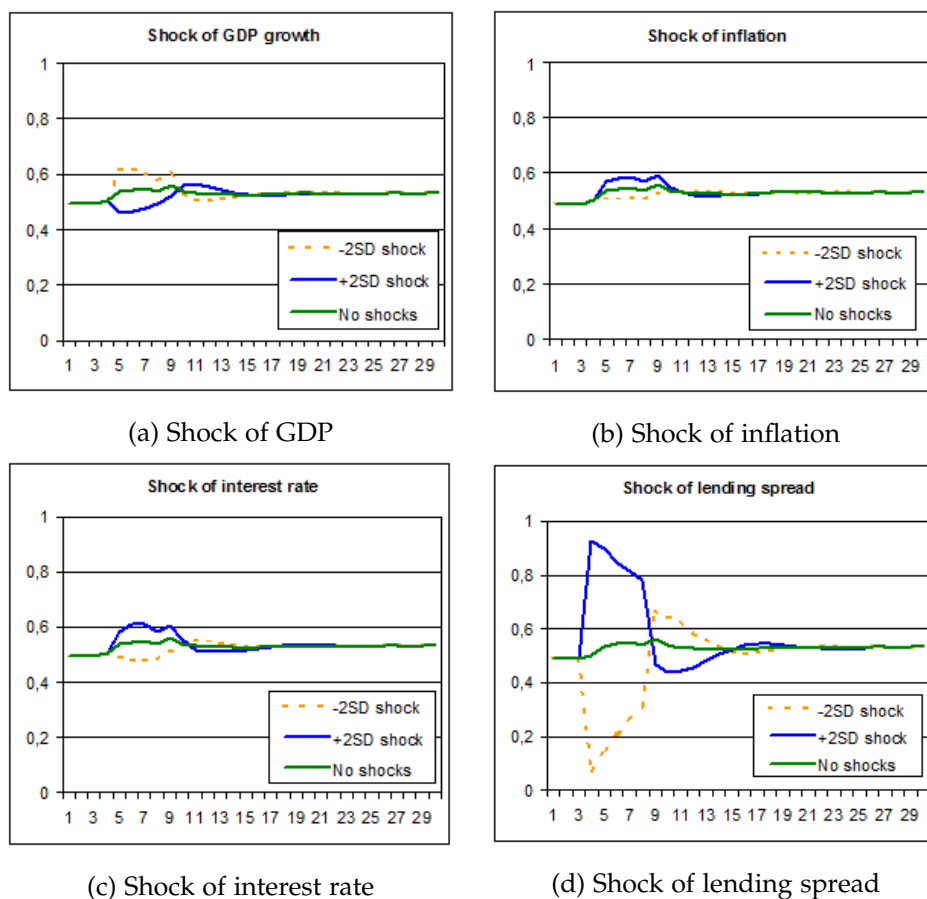
Figure 17: Probability to be in the *stressed* credit regime following two standard errors deviation shocks

present in Figure 17 the weighted average of responses across regimes.[24]

We notice that excepting credit variable shocks, even two standard deviations shocks of inflation, GDP and interest rate have a low impact on the probability of being in the un-favourable credit regime. Indeed, a large unfavourable shock (+2SD) to the lending spread can raise the probability of being in the *stressed* credit regime by more than 30 p.p. However, even if being of lower impact, GDP shocks have an impact of almost 7 p.p. on this probability. Therefore, model B shows mild evidence of the importance of other economic shocks for the evolution of credit regimes.

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[24]Weight for the *standard* (resp. *stressed*) regime corresponds to the percentage of periods identified as being in the *standard* (resp. *stressed*) credit regime.

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Lastly, convergence to the long run probability is achieved after 10 quarters (excluding the first three quarters corresponding to the transmission delay of shocks to the indicator function).

Appendix D GIRFs bootstrapping algorithm

The TVAR model being non-linear, responses of endogenous variables depend on initial conditions and past history. To overcome this issue and be able to evaluate history independent response of endogenous variables, we turn to Koop, Pesaran and Potter (1996) methodology. Denote K the maximum horizon.

1. The set of possible initial conditions over Y is separated into two sets according to each possible regime. We construct $\mathcal{IC}_0 = \{Y_t | \mathbb{1}_{c_{t-d} \geqslant \gamma} = 0\}$ and $\mathcal{IC}_1 = \{Y_t | \mathbb{1}_{c_{t-d} \geqslant \gamma} = 1\}$. We will compute two generalised impulse responses to the shock u_t, conditionally on each initial regime.

2. For each subset of initial conditions $\mathcal{IC}$, repeat steps 3 to 7

3. For each initial conditions ic_t in the chosen subset $\mathcal{IC}$, repeat steps 4 to 6 a large number of times (N=500)

4. Draw a time series of shocks $\hat{\varepsilon}_s$ for $s = 1 \ldots K$ from the estimated TVAR residuals, and $\forall k \in \{1 \ldots K\}$, simulate the path $Y_{t+k} | ic_t, \{\hat{\varepsilon}_s\}_{s=1 \ldots k}$ with respect to the selected initial condition ic and the series $\{\hat{\varepsilon}_s\}_{s=1 \ldots k}$.

5. $\forall k \in \{1 \ldots K\}$, similarly compute $Y_{t+k} | u_t, ic_t, \{\hat{\varepsilon}_s\}_{s=1 \ldots k}$ adding a one standard deviation shock u_t at time t.

6. Compute the impulse response conditional on ic_t and $\{\hat{\varepsilon}_k\}_{k=1 \ldots K}$

$$GIRF_k(u_t | ic, \{\hat{\varepsilon}_s\}_{s=1 \ldots k}) = Y_{t+k} | u_t, ic_t, \{\hat{\varepsilon}_s\}_{s=1 \ldots k} - Y_{t+k} | ic_t, \{\hat{\varepsilon}_s\}_{s=1 \ldots k} \tag{10}$$

7. Compute the generalised (unconditional) impulse response by averaging $GIRF_k(u_t)$ over all initial conditions and all bootstrapped shocks series.

Appendix E Balke (2000) non-linear contribution methodology

In a linear model, it is equivalent to dynamically simulate the model with one type of shocks at a time (here GDP, inflation, interest rate or credit conditions) and add them ex post, or to

simulate with multiple shocks. Due to the linearity property, the four independent contributions[25] add up to the observed value of GDP growth.

In a non-linear model, this adding up property does not hold any longer and the analysis of contributions appears more complicated. Relying on the previous approach, Balke (2000) proposes a decomposition methodology. He computes the dynamically simulated GDP growth for each type of shocks. The remaining difference between the sum of the four contributions and the observed value of GDP growth, quoting:

"reflects the interaction among the shocks that is inherent in the non-linear structure of the threshold VAR. [...] the remainder term represents, in part, the contribution of switching credit regimes to the non-linear propagation of shocks."

However, this interpretation of the remainder as the contribution of non-linearity to GDP growth is misleading. It is indeed only accounting *"in part"* for non-linearities. Actually, each of the *standard* four contributions[26] also includes switching regimes and a non-linear propagation of shocks in the economy. Therefore, the remainder cannot be interpreted neither as a lower or upper bound to the economic effect of non-linearities in the propagation of shocks. As a result, we depart in our study from this methodology, and study contributions of credit shocks in a different framework.

Appendix F   Estimated coefficients

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[25]Formally, we also need to include an exponentially converging initial condition representing the propagation of the first observed value in the absence of shocks.

[26]Denominated Change in the forecast Function in Balke (2000).

(a) Coefficients

	Constant	VCAC40(t)	GDP(t)	Inflation(t)	R(t)	VCAC40(t-1)	GDP(t-1)	Inflation(t-1)	R(t-1)
	C	A				B			
VCAC40(t)	0,03	0	0	0	0	0,15	-0,01	0,43	0,00
ΔlnGDP(t)	0,25	-1,87	0	0	0	-1,72	0,61	3,11	-0,35
Inflation(t)	0,00	-0,02	0,00	0	0	0,01	0,00	0,45	0,00
ΔR(t)	-0,23	-0,76	0,08	9,29	0	-0,46	0,17	14,29	0,25

(b) T-stat

	Constant	VCAC40(t)	GDP(t)	Inflation(t)	R(t)	VCAC40(t-1)	GDP(t-1)	Inflation(t-1)	R(t-1)
	C	A				B			
VCAC40(t)	5,21					1,49	-1,49	0,56	0,65
ΔlnGDP(t)	1,83	-0,93				-0,85	7,37	0,20	-2,94
Inflation(t)	2,71	-1,85	0,89			1,21	1,04	4,94	0,38
ΔR(t)	-1,98	-0,47	0,99	0,70		-0,29	2,05	1,08	2,59

Table 6: Estimation results for linear model A

(a) Coefficients

	Constant	Spread(t)	GDP(t)	Inflation(t)	R(t)	Spread(t-1)	GDP(t-1)	Inflation(t-1)	R(t-1)
	C1		A1				B1		
ΔSpread(t)	0,33	0	0	0	0	-0,08	-0,57	6,56	0,60
ΔlnGDP(t)	0,26	-0,40	0	0	0	0,22	0,43	3,15	-0,20
Inflation(t)	0,00	0,00	0,00	0	0	0,00	0,00	0,36	0,00
ΔR(t)	-0,12	-0,14	0,04	6,30	0	-0,25	0,12	4,67	0,33
	C2		A2				B2		
ΔSpread(t)	-0,56	0	0	0	0	-0,01	0,70	8,18	-0,81
ΔlnGDP(t)	-0,01	0,52	0	0	0	-0,46	0,13	-12,69	0,12
Inflation(t)	0,00	0,00	0,00	0	0	0,00	0,00	0,20	0,00
ΔR(t)	-0,10	0,25	0,18	-5,70	0	-0,20	-0,33	20,30	-0,06

(b) T-stat

	Constant	Spread(t)	GDP(t)	Inflation(t)	R(t)	Spread(t-1)	GDP(t-1)	Inflation(t-1)	R(t-1)
	C1		A1				B1		
ΔSpread(t)	2,24					-0,59	-3,99	0,25	3,19
ΔlnGDP(t)	2,21	-3,72				2,18	3,42	0,16	-1,28
Inflation(t)	3,68	-1,20	-0,15			0,02	0,63	2,68	0,33
ΔR(t)	-1,14	-1,49	0,39	0,44		-3,19	1,09	0,29	2,68
	C2		A2				B2		
ΔSpread(t)	-2,62					-0,07	3,47	0,24	-3,12
ΔlnGDP(t)	-0,03	3,46				-3,19	0,81	-0,48	0,57
Inflation(t)	-1,99	0,39	0,82			1,18	0,39	1,10	-0,77
ΔR(t)	-0,68	1,99	1,16	-0,24		-1,71	-2,22	0,86	-0,37

Table 7: Estimation results for model B

Appendix G   Impulse Response Functions in model A

(a) Response of GDP

(b) Response of inflation

(c) Response of the interest rate

(d) Response of the VCAC40
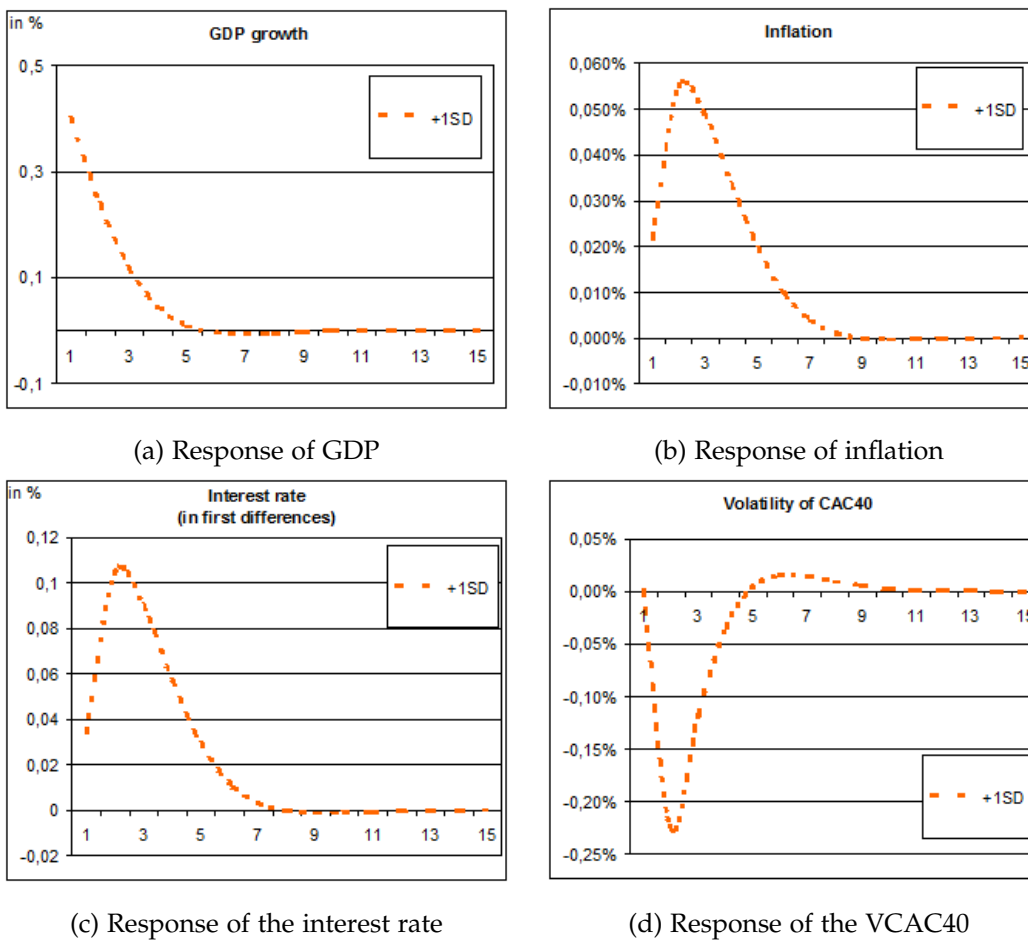
Figure 18: Impulse Responses to a one standard error deviation shock of GDP growth

(a) Response of GDP

(b) Response of inflation

(c) Response of the interest rate

(d) Response of the VCAC40
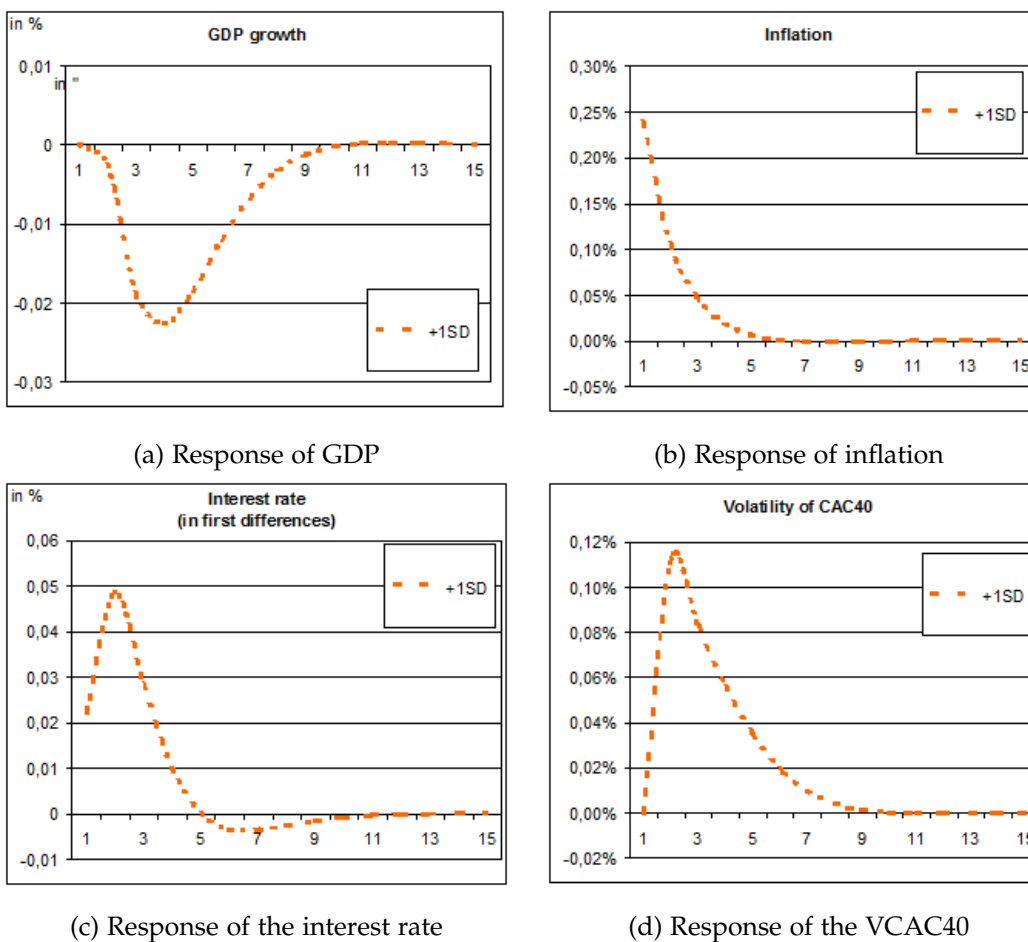
Figure 19: Impulse Responses to a one standard error deviation shock of inflation
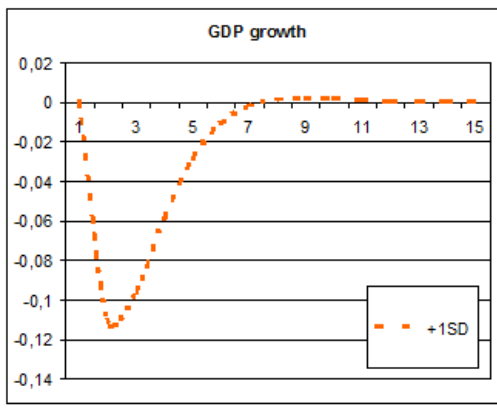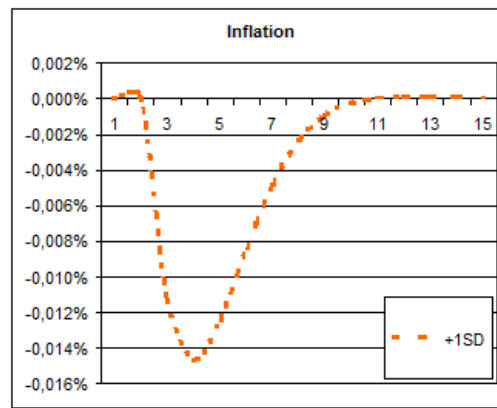
(a) Response of GDP   (b) Response of inflation
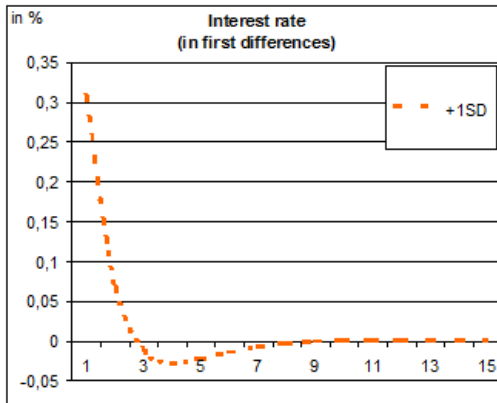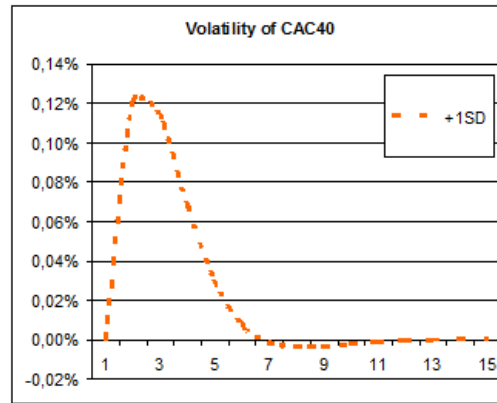
(c) Response of the interest rate   (d) Response of the VCAC40

Figure 20: Impulse Responses to a one standard error deviation shock of the first difference of the interest rate
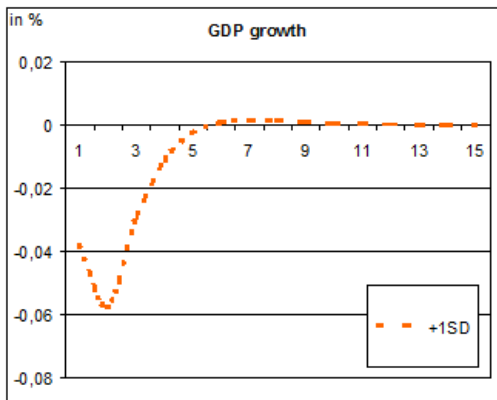
(a) Response of GDP   (b) Response of inflation
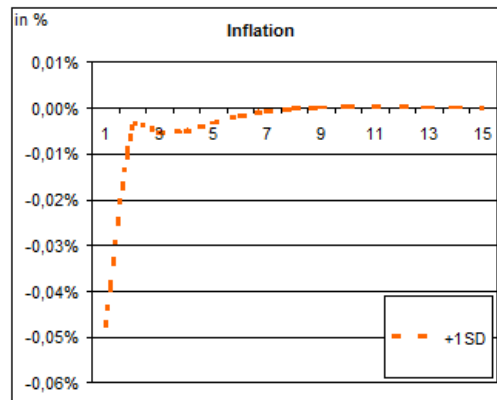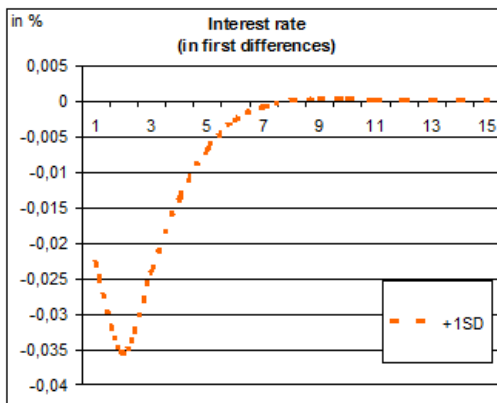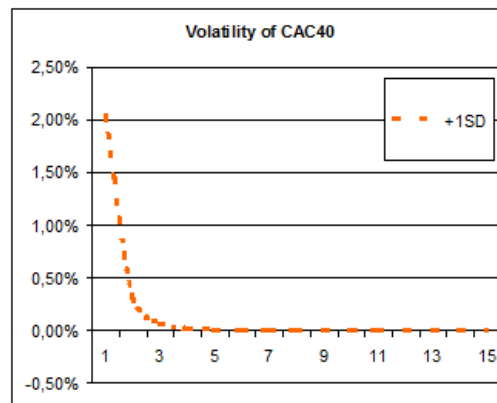
(c) Response of the interest rate   (d) Response of the VCAC40

Figure 21: Impulse Responses to a one standard error deviation shock of VCAC40

Appendix H   Impulse Response Functions in model B

(a) Response of GDP - Initial *standard* regime

(b) Response of GDP - Initial *stressed* regime

(c) Response of inflation - Initial *standard* regime

(d) Response of inflation - Initial *stressed* regime

(e) Response of the interest rate - Initial *standard* regime

(f) Response of the interest rate - Initial *stressed* regime

(g) Response of the lending spread - Initial *standard* regime

(h) Response of the lending spread - Initial *stressed* regime

Figure 22: Impulse Responses to a one standard error deviation shock of GDP growth

(a) Response of GDP - Initial *standard* regime

(b) Response of GDP - Initial *stressed* regime

(c) Response of inflation - Initial *standard* regime

(d) Response of inflation - Initial *stressed* regime

(e) Response of the interest rate - Initial *standard* regime

(f) Response of the interest rate - Initial *stressed* regime

(g) Response of the lending spread - Initial *standard* regime

(h) Response of the lending spread - Initial *stressed* regime

Figure 23: Impulse Responses to a one standard error deviation shock of inflation
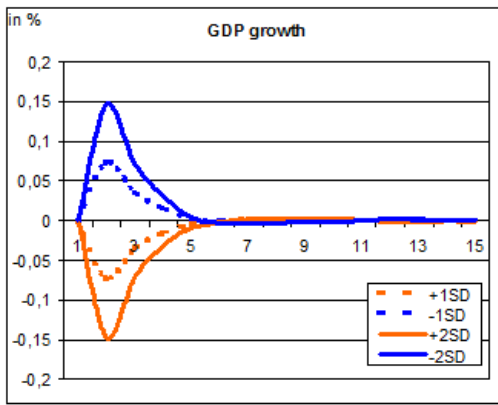
(a) Response of GDP - Initial *standard* regime
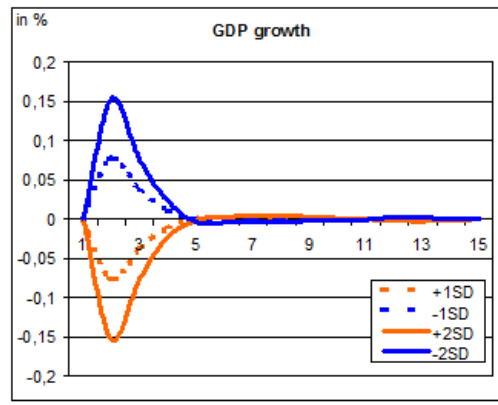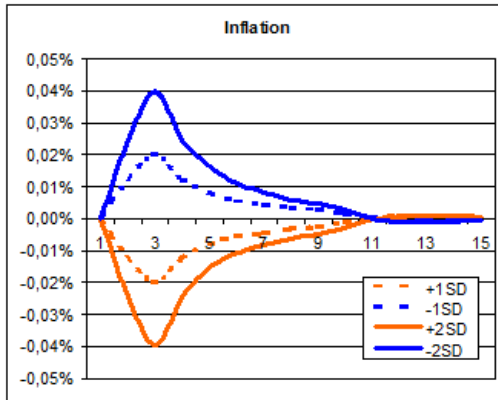
(b) Response of GDP - Initial *stressed* regime

(c) Response of inflation - Initial *standard* regime
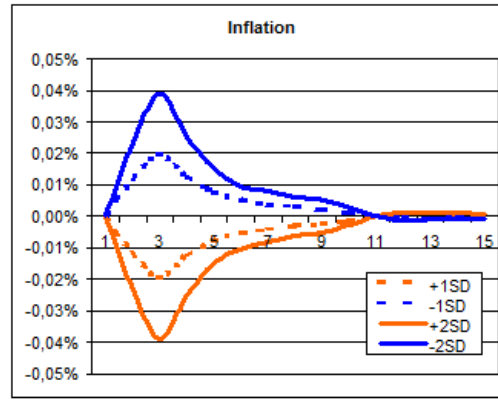
(d) Response of inflation - Initial *stressed* regime
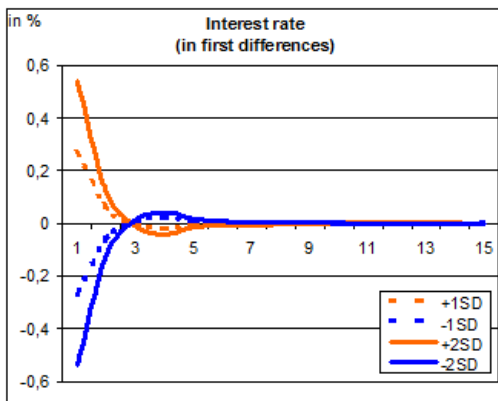
(e) Response of the interest rate - Initial *standard* regime
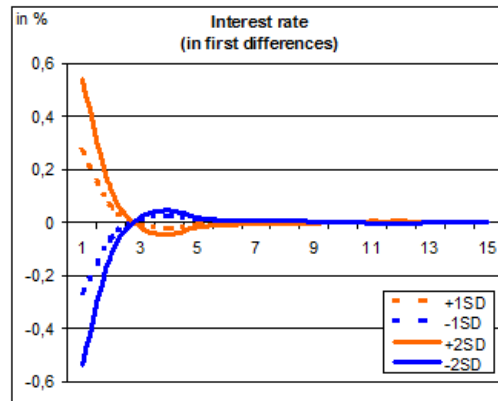
(f) Response of the interest rate - Initial *stressed* regime
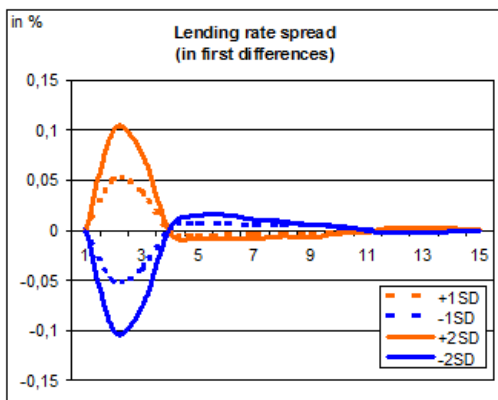
(g) Response of the lending spread - Initial *standard* regime
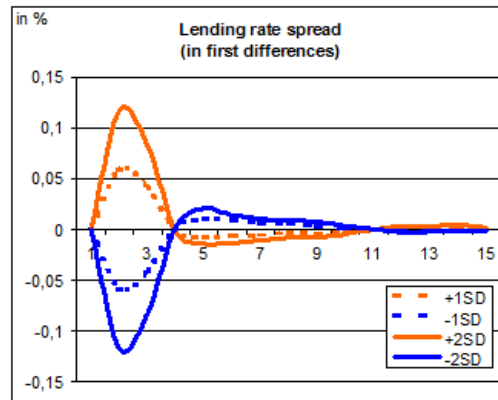
(h) Response of the lending spread - Initial *stressed* regime

Figure 24: Impulse Responses to a one standard error deviation shock of the interest rate (in first differences)
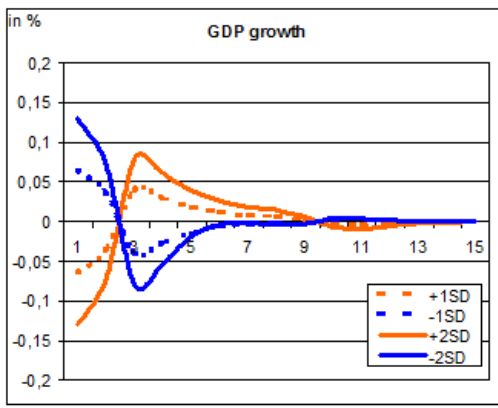
(a) Response of GDP - Initial *standard* regime
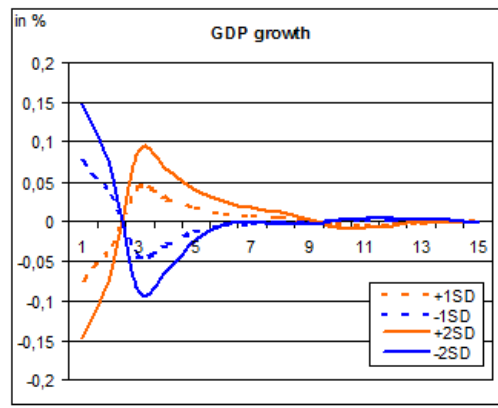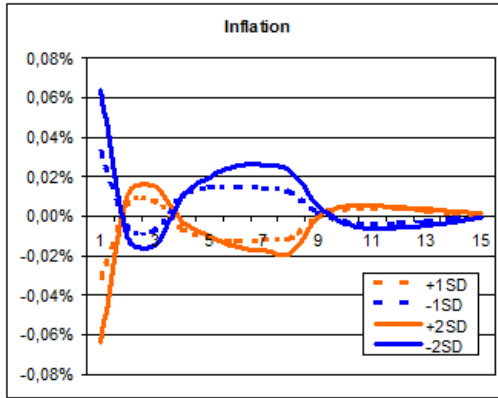
(b) Response of GDP - Initial *stressed* regime

(c) Response of inflation - Initial *standard* regime
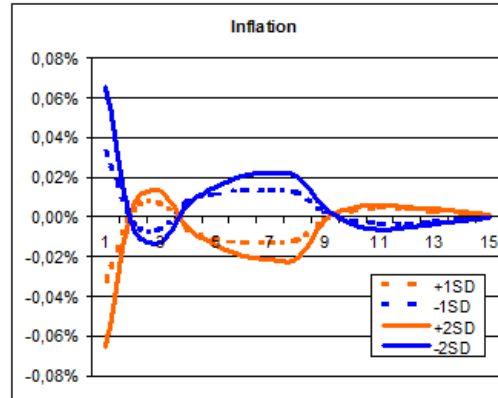
(d) Response of inflation - Initial *stressed* regime
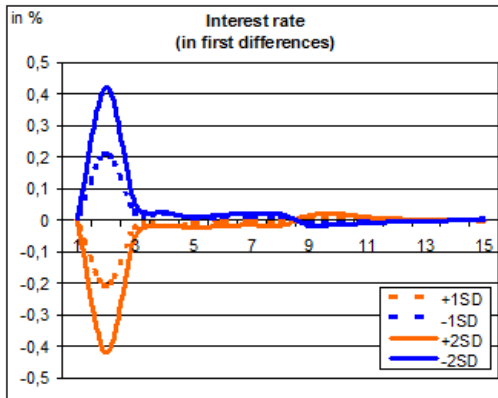
(e) Response of the interest rate - Initial *standard* regime
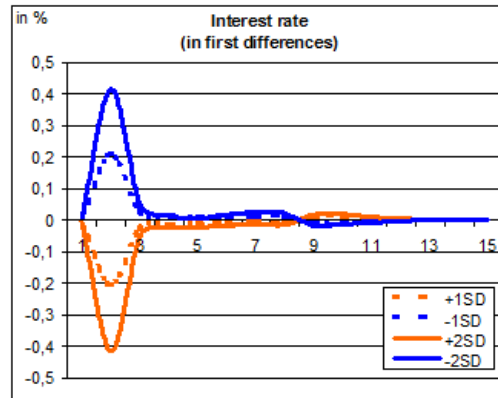
(f) Response of the interest rate - Initial *stressed* regime
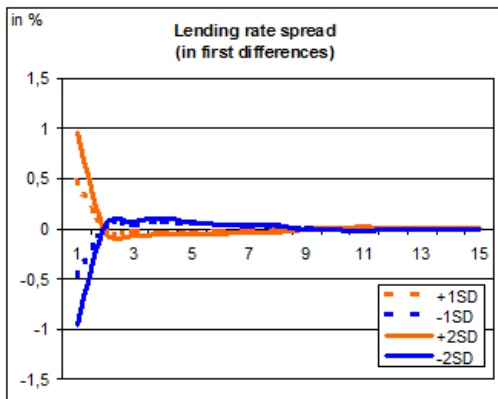
(g) Response of the lending spread - Initial *standard* regime
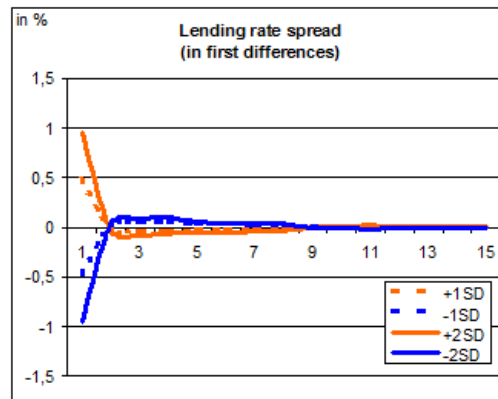
(h) Response of the lending spread - Initial *stressed* regime

Figure 25: Impulse Responses to a one standard error deviation shock of lending spread (in first differences)

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