Credit procyclicality and financial structure in EU

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Aurélien Leroy*

October 21, 2014

Abstract

This paper empirically analyzes the linkages between credit procyclicality and financial architecture in Europe over the time period from 1999 to 2012 using panel VAR model with interaction terms. This framework allows to make response of credit to an real activity shock conditional to the financial structure of the different economies. Based on financial accelerator theory we presume that 4 indicators of country’s financial architecture (bank competition, bank business model, nature of the financial system as well as risk-weighted capital) can mitigate asymmetry information problems and alleviate incentives to risk-taking. Our findings show that bank competition (low concentration), bank-based financial system as well as well capitalized system imply a weaker procyclicality of bank credit, that we consider as an evidence of a higher stability. Results for bank business model are more mixed. The findings suggest that financial structures matter for stability and for business cycle. Since we assume procyclicality as a measure of instability, our contribution is related to the literature analyzing the effects of financial structures on stability.

Keywords: Credit cycle, Economic cycle, stability, financial structure, bank competition, Interacted panel VAR

JEL Codes: C33, E51, E52

*Laboratoire d’Economie d’Orléans (LEO), UMR CNRS 7322, Rue de Blois, BP 26739, 45062 Orléans Cedex 2, France. E-mail: aurelien.leroy@univ-orleans.fr
1 Introduction

The question of the linkage between instability and financial architecture has been at the heart of academic and political discussions since the eruption of the Global Financial Crisis. In response to the crisis, the European Commission has pursued a number of initiatives to create a safer and sounder financial sector for the single market. These initiatives led to the foundation of a Banking Union for instance which includes the establishment of a Single Supervisory Mechanism and of a Single Resolution Mechanism, but also of the improvement of bank prudential requirement in all European Union Member States. In addition the European Commission is pursuing project to modify and harmonize financial structures. On this topic, numerous papers or reports have assessed whether structural reforms of the financial system would reduce the probability of a financial crisis.

The focus of politics and academics on these questions is explained by the fact that the effects of financial instability do not only lead to adverse consequences for the financial sector, but affects the entire economy. Thus, although economic growth is undeniably dependent to real factors as labor productivity, physical capital stock for instance, several historical experiences as well as academic research have (progressively) highlighted the preponderant role of financial factors on the real economic activity.

In this regard, the experience of the Great Depression is a particularly poignant case study for academics. Bernanke (1983) argues that the financial collapse of 1930-33 reduced the bank allocation efficiency, increased real cost of financial intermediation and led to a credit squeeze which reduced aggregate demand. According to Bernanke this non-monetary explanation of the crisis allows to understand the unusual length and scale of the Great Depression. This crisis experience shows that financial systems are not just a passive reflection of real sector, but can be a source of real economic activity downturn.\footnote{Several empirical studies highlight the macroeconomic effects of adverse shocks to bank loan supply, see among others Bernanke and Lown (1991), Ashcraft (2005), Lown and Morgan (2006) and Bassett et al. (2010).}

Bernanke (1983) suggests that market frictions as asymmetric information problems, are a natural way to explain the propagation of small shocks to the financial sphere. Bernanke and Gertler (1989) formalize these ideas into the concept of financial accelerator. The financial accelerator can be summarize as follow. First of all, the economy is hurt by an aggregate economic activity shock that causes a change of the net worth of potential borrowers. Due to asymmetric information the deterioration of net worth leads...
to an increase of external finance premium.\textsuperscript{2} Therefore, credit becomes more expensive and/or has a reduced availability during a recession. This first step of financial accelerator theory allows to understand procyclicality of financial system, that is the fact that credit cycles are more pronounced than real economic cycles. Second, it follows that this procyclicality of bank lending tends to amplify the real economic cycle owing to the weakening of investment for instance.\textsuperscript{3} As a result, financial accelerator theory is based on two mechanisms: a propagation and an amplification mechanisms.

The original idea of this paper is to consider the credit procyclicality which explains the propagation mechanism, as a measure of financial instability. The more the procyclicality of the system, the more important the underlying instability is. This insight appears relatively well documented since it has been empirically observed that credit booms lead to financial crisis (see, Kindleberger and Aliber, 2011). However with the exception of the contribution of Bouvatier et al. (2012), no study considers procyclicality as a measure of financial instability. Typically, studies prefer to use as a measures of banking instability indicators based on bank-balance-sheet information (Non Performing Loans, Z-score), market prices (Distance to default, SRISK) or banking crisis. However in our view, credit procyclicality has two comparative advantages. First, it allows to assess underlying instability, which is, on the one hand, not necessarily apparent in other proxies based on bank balance-sheet information or market prices and, on the other hand, not necessarily well estimated when the financial instability is built on bank crisis prediction works.\textsuperscript{4} In addition, the amplification mechanism of the financial accelerator offers theoretical foundations for our analysis and allows directly to rely credit procyclicality to real economic costs. Indeed, if banking sector is scrutinized it is only due to the consequence of the fluctuations of availability of the credit on the real economy. The absolute level of risk is not really relevant.

This paper asks what drives credit procyclicality in EU and for this purpose we focus on financial structures. Thus, our objective is to define the “best” financial architecture in term of stability for European Union economies. In our view the ideal financial structure should smooth procyclicality and consequently feedback effects on the real sphere. Thus

\textsuperscript{2}External finance premium is defined as the cost of external funds minus the opportunity costs of internal funds. The explanation to the inverse relationship between intermediation premium and net worth, is that the reduction of agents' wealth increases agency problems because the interests between the principal and the agent diverge when the wealth raises in the project by the agent diminish which implies an increase of agency premium

\textsuperscript{3}Minsky (1986)'s insights are nearly orthogonal to this view. In Minsky's view, the firms ability to raise external funding depends on internal net worth and firm's balance-sheet fluctuations that affects firm investment. However Minsky's microfoundations differ greatly since the link between investment and availability of financing is not explain by asymmetric information.

\textsuperscript{4}This is in part due to the very limited number of systemic crisis in EU over the time.
according to the financial accelerator theory, we attempt to determine the system which
the best solves the asymmetric information problems. Also, more in line with Minsky
view, the ideal system should allow a better appreciation of the risks and low risk-taking
incentives.
To tackle the question of factors underlying the heterogeneity of the credit procyclicality,
we proceed in three steps. First, we highlight different levels of procyclicality between
EU countries. Second, we check the existence of a financial accelerator mechanism in
EU. Finally, we tend to explain the heterogeneity of procyclicality by the structural
characteristics of banking systems. In this regard, we define a set of 4 indicators in order
to proxy all the dimensions of the financial architecture. We consider, bank competition,
bank business model, bank or market based financial system and last regulatory capital.
From a methodological point of view, to analyze the credit procyclicality and in particu-
lar what drives procyclicality, we employ two different type of panel vector autoregressive
(P-VAR) model for 14 EU members over the period 2000-2012. The first panel-VAR
model refers to the approach used by Canova and Ciccarelli (2009) for instance, and al-
 lows to assess the average financial accelerator mechanism in EU. In this case our panel-
VAR model includes homogeneous parameters and fixed effects. Thus, we consider that
the source of heterogeneity is exclusively inobservable. The second panel-VAR model
used is a panel-VAR with interaction terms. The approach allows to model explicitly the
heterogeneity in the extent to VAR coefficients are allow to vary with country-specific
structural characteristics. As a result in our case, this framework makes that the impulse
responses of bank credit to an activity shock (propagation mechanism) are conditioned
on countries’ financial structure indicators. Such a framework has been recently de-
veloped and used by Loayza and Raddatz (2007), Sá et al. (2014), Towbin and Weber
(2013) or Georgiadis (2014).
Our empirical analysis allows to highlight that the co-movements between bank credit
and business cycles are very divergent in EU. Different linkages between credit markets
and short-run output fluctuations are both an explanation and a consequence of the
different intensity of the recent crisis. Our analysis also confirms the existence of the
two mechanisms of the financial accelerator in EU. Activity shocks influence bank credit
in a procyclical way and bank credit has feedback effects on real activity, which amplify
the cycle. Last, our findings allow to understand what drives procyclicality in EU. We
find that banking competition, the focus on traditional bank activities, bank-based na-
ture of the financial systems as well as the high capitalization of banking systems reduce
significantly the procyclicality of bank credit. This conclusion suggests that the financial
architecture described is the most appropriated to reduce macroeconomic volatility.
The remainder of the paper is structured as follows. Section 2 starts by assessing the heterogeneity of co-movement between business and credit cycles in EU. The next section presents the different indicators of financial structures used in this study. In section 4, we present the empirical analysis, discussing the data used, the identification strategy and the estimation methodology. The results are reported in section 5 and section 6 looks at the robustness of these results. Finally, the last section concludes.

2 Cross-country heterogeneity of credit procyclicality in EU

In this first section, we present statistical evidences of co-movement between credit and output cycles in EU. To achieve this, we have to determine credit and output cycles. In this study, we use univariate statistical methodologies to decompose macroeconomic data into a cyclical component and a trend. Especially, we use the Hodrick and Prescott (1980, 1997) filter (hereafter the HP filter), which is the standard method for removing trend movements in the business cycle literature. The main advantage of the methodology is its ease of calculation and interpretation. Thus the HP filter technique consists of fitting the trend \( \tau_t \) of a time series \( y_t \) by solving the following minimization problem:

\[
\min_{\tau_t} = \sum_{t=1}^{T} ((y_t - \tau_t)^2 + \lambda((\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}))^2) \tag{1}
\]

The minimization problem has two terms. The first measures the goodness of the fit and the second penalizes changes in the trend according to the smooth parameter, \( \lambda \).

The deviation from the trend \( (\tau_t - y_t = \varepsilon_t) \), that is the residual, is commonly considered as the cyclical component of the time series.

As shown by Kaiser and Maravall (2001) for instance, the use of HP filter has been subject to several criticisms. The main is linked to the end point problem. At the end of the period, we observe that the trend \( \tau_t \) tends to be near to the observed data \( y_t \).

It appears that this problem is more significant when the observed data are far from the trend at the extremity of the considered period. Baxter and King (1999) suggest to drop some end points to fix the problem. Another drawback of HP filter underlined in the literature is the amount of noise in the cyclical signal.

To overcome criticisms of HP filter we check throughout our paper our results by considering two other ways to measure the cycle.

First, we extend our series of 4 quarters at both end points to re-build more robust
filtered series. This is possible since our study period (1999-2012) is constrained by the availability of financial structural data (see next section) and not by macroeconomic data.6

Second, we consider the Christiano and Fitzgerald (2003) band pass procedure that extend the Baxter and King (1999) filter.

On the graph 1, we report our HP-filtered series of GDP and bank credit for all EU countries.

As can be observed on the previous figures and as expected output and credit cycles evolve in the same direction. To observe explicitly co-movement and take in evidence heterogeneity we report in table 1 the correlations between credit and business cycles obtain from HP filtering series. The correlation coefficients indicate that these two se-

6Another way to do the same is to employ the Kaiser and Maravall (1999) HP-filter. The main features of this modified HP filter is that is combined the traditional HP filter technique and ARIMA model. The ARIMA model allows to generate forecasts to extend the series at both end points. However estimating HP filter on a higher series and then truncating the filter as we do is preferable since ARIMA forecasts are not without errors.
eries evolve in the same direction and that this effect is statistically significant. The table displays different correlation coefficients. As can be seen, the correlations are more important and significantly higher when we consider one or two forward values of credit cycle (compared to GDP cycle). These stylized facts might suggest that GDP cycles precede credit cycles but leave open the question of causality. Among EU’s countries, the UK and Sweden seem very singular. Indeed, their correlation coefficients are the weakest and the two only not significant. Globally, we observe an important heterogeneity between the countries that raises questions about the factors underlying that.

Table 1: Correlation between HP-filtered GDP and bank Credit

<table>
<thead>
<tr>
<th></th>
<th>AUT</th>
<th>BEL</th>
<th>DNK</th>
<th>FIN</th>
<th>FR</th>
<th>GER</th>
<th>GRE</th>
<th>IRE</th>
<th>IT</th>
<th>NTH</th>
<th>PT</th>
<th>SP</th>
<th>SWE</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i=-2$</td>
<td>0.3826*</td>
<td>0.6762*</td>
<td>0.1698</td>
<td>0.0227</td>
<td>0.2910*</td>
<td>0.5607*</td>
<td>0.3843*</td>
<td>0.5579*</td>
<td>0.5518*</td>
<td>0.4653*</td>
<td>0.7262*</td>
<td>-0.1761</td>
<td>0.2346</td>
<td></td>
</tr>
<tr>
<td>$i=-1$</td>
<td>0.2803*</td>
<td>0.4475*</td>
<td>0.0221</td>
<td>-0.1447</td>
<td>0.0489</td>
<td>0.5023*</td>
<td>0.2549</td>
<td>0.3291*</td>
<td>0.3310</td>
<td>0.3253</td>
<td>0.6366</td>
<td>-0.3495</td>
<td>0.1301</td>
<td></td>
</tr>
<tr>
<td>$i=0$</td>
<td>0.4654*</td>
<td>0.7962*</td>
<td>0.3176*</td>
<td>0.2249</td>
<td>0.4676*</td>
<td>0.6323*</td>
<td>0.4676*</td>
<td>0.6742*</td>
<td>0.6952*</td>
<td>0.5758*</td>
<td>0.7593*</td>
<td>-0.3455</td>
<td>0.2235</td>
<td></td>
</tr>
<tr>
<td>$i=1$</td>
<td>0.5047*</td>
<td>0.8131*</td>
<td>0.4551*</td>
<td>0.3981*</td>
<td>0.5161*</td>
<td>0.6975*</td>
<td>0.5060*</td>
<td>0.6828*</td>
<td>0.6586*</td>
<td>0.5615*</td>
<td>0.7457*</td>
<td>0.1996</td>
<td>0.1362</td>
<td></td>
</tr>
<tr>
<td>$i=2$</td>
<td>0.5037*</td>
<td>0.7431*</td>
<td>0.5314*</td>
<td>0.5264*</td>
<td>0.6529*</td>
<td>0.7280*</td>
<td>0.5900*</td>
<td>0.6077*</td>
<td>0.5065*</td>
<td>0.5106*</td>
<td>0.7148*</td>
<td>0.3489*</td>
<td>0.0312</td>
<td></td>
</tr>
</tbody>
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Note: Asterix indicates that the correlation coefficient is significantly different from zero using at 5% level.

As shown by Den Haan (2000) and Den Haan and Sumner (2004) the measure of unconditional correlations have some weaknesses. Especially, it leads to a lose of valuable information about the dynamic of correlations since it focuses only on one correlation coefficient. Den Haan (2000) proposes two methodologies to obtain dynamic correlation. The first is based on VAR methodology and the second uses band-pass filter from the frequency domain proposed by Baxter and King (1999). In this study, we opt for VAR methodology to capture the dynamic correlation of credit and output cycles. Following Den Haan (2000); Den Haan and Sumner (2004) firstly we estimate the fol-
ollowing VAR for each country:

\[ X_t = \alpha + \sum_{l=1}^{4} A_l X_{t-l} + \varepsilon_t \]  

(2)

where \( X_t \) is a vector containing the output and credit cycles, respectively \( Y \) and \( C \), \( A_l \) a matrix of regression coefficients. Due to the short temporal observations, the maximum number of lags is fixed to 4 and we select the optimal lags based on AIC criterion.

Secondly we compute the \( k \)-period ahead forecast errors for \( Y \) and \( C \). The \( k \)-ahead forecast errors can be written as:

\[ X_{t+k,t}^{fer} = (X_{t+k} - X_{t+k,t+k-1}^f) + (X_{t+k,t+k-1}^f - X_{t+k,t+k-2}^f) + \ldots + (X_{t+k,t+1}^f - X_{t+k,t}^f) \]  

(3)

To obtain a dynamic measure of correlation we use the time series of forecast errors of \( Y \) and \( C \) at \( k \) different horizons and we calculate the correlation for each horizon \( (COR(k)) \).

3 Assessing financial structures in EU

Our main hypothesis in this paper is that financial structures affect the credit procyclicality and can explain the different scales of co-movement between bank credit and activity in EU.

First, we have to define what we mean by financial structures. Indeed this term is broad and not particularly defined in the literature. In order to have a complete view, we consider four different structural characteristics related to the credit supply side: bank competition, bank business model, nature of the financial system and bank capital.

**Banking sector competition**

As argued by Keeley (1990) among others, banking competition can affect the stability of the financial sector. Keeley (1990) finds that the increase of competition in the US in the 80s, has pushed (prompted) banks to take more risks, by reducing capital ratio and increasing the bank asset portfolio risks. The erosion of monopoly rents would reduce bank charter values leading to an increase of moral hazard incentives (Hellmann et al., 2000) due to the decrease of bankruptcy opportunity costs (Northcott, 2004). In this view, low competition implies that banks will hold more capital, less risky assets and a
Figure 2: Correlation Coefficients between Business and Credit cycles in UE
smaller loan portfolio. Thus, bank fluctuations should be less pronounced when banking competition pressure is low.

However, in the opposite the competition-stability strand underlines that bank market power increases the instability since market power implies that banks charge higher rates. As shown by Stiglitz and Weiss (1981) higher interest rates can increase the risk of bank portfolio because of adverse selection and moral hazard problems. Boyd and De Nicolo (2005) demonstrate that this effect implies no trade-off between competition and stability. Caminal and Matutes (2002) have the same conclusion but another explanation. They show that monopoly banks choose risky assets because they incur monitoring costs.

Competition can also impact stability through its effects on the orientation of banks (transaction vs. relationship oriented banking). Indeed, relationship lending would increase the information held by banks that would give long-term informational rents. As a result, the banks can manage risk more efficiently and reduce asymmetric information problems. Furthermore, a relationship banking system can allow intertemporal smoothing of contract terms. Relationship lending based system may be more likely to reduce margins in downturn period, and limiting the fall of bank credit in the extent to these short-run losses will be recover later (Berlin and Mester, 1998; Petersen and Rajan, 1994). All this means that the relationship oriented banking system would be less procyclical.

The traditional view is that more competition leads to less relationship banking (Petersen and Rajan, 1995). Indeed, fierce competition implies that borrowers can easily switch to another bank that reduces incentives to collect private information and to offer subsidies to borrowers (Chan et al., 1986). However, an alternative view is that competition can reinforce relationships since that allows banks to alleviate this competitive pressure (Boot and Thakor, 2000).

Given the conflicting theoretical effects of banking competition, there are many empirical contributions which try to give clearer conclusions about the effects of bank competition on stability. However empirical evidences do not allow to close the debate. Whereas, Beck et al. (2006) or Jiménez et al. (2007) find the existence of a trade-off between competition and stability, other studies find that greater competition stabilize the banking system because banks hold more capital (Nicoló et al., 2006; Berger et al., 2009; Schaeck et al., 2009), are more efficient (Schaeck and Cihák, 2014) or have more diver-

\footnote{Berlin and Mester (1998) note that the stability of deposit rates in relationship bank system allows bank to smooth creditor interest rates. For their part, Petersen and Rajan (1994) show intertemporal subsidies are essential for SME funding.}
sified risks (Anginer et al., 2013). Closer to the study carried out in this paper since it is a macro-level study which focuses on the EU, Uhde and Heimeshoff (2009) show that concentration in EU goes hand in hand with financial instability.

As discussed above, competition could impact the stability and the procyclicality of banking credit. To test this effect in this study, we need to choose a proxy for the degree of banking competition of an economy. The main issue is there are many different measures of banking competition in the literature and no consensus regarding the “best” indicator (Northcott, 2004). Nevertheless, it appears that there is a clear distinction between indicators based on the structure conduct performance and the efficient structure paradigms. In the first paradigm, market structures are assumed to influence bank behavior. In this view, concentration ratio would provide an appropriate proxy of competition. However, this has been criticized. Claessens and Laeven (2004) argue that concentration ratios do not allow to gauge correctly the competitiveness of a banking sector. To address the criticism, the second paradigm dissociates concentration to competition, and proposes other proxies not based on structures but directly on bank behavior, that we can observe through the bank balance-sheet information. Among these indicators, we can cite the Lerner Index, the net interest margin, the H-statistic or the Boone indicator.

Due to lack of consensus, for the measurement of banking competition, we select four different indicators and build a composite index of banking competition. Two of the four selected variables rely on SCP paradigm. Actually, we consider the Herfindahl-Hirschman Index (HHI) and a concentration ratio of the five bigger banks. Since concentration has some limits, we include in more the net interest margin (loan minus deposit rate) and the Lerner Index (bank average revenue minus bank marginal cost divide by average revenue). These two latter indicators measure the market power. As shown from a theoretical point of view these four indicators can give some redundant information.

To combine our indicators into a single index, and to allow data reduction, we have two alternatives. First, we can assign an equal weight to each variables as Georgiadis (2014). The second alternative is to make a principal component analysis (hereafter PCA), which allows to evaluate the optimal weight of each variable in the composite index to explain the most of the variance of the variables (highest joint R-square).

We select for our baseline model PCA since that allows to best explaining the four competition indicators. Nevertheless since the correlation matrix reveals that the two concentration ratios and the two others competition indicators are weakly correlated, we implement in a robustness check an equal weight index.

For PCA, we retain the two first components. This choice is based on Kaiser criterion
which recommends to keep only components with eigenvalues higher than 1. We have also checked that the second retained component explains a significant percentage of the variance. In our case the second component explains 27.80% of the total variance and the first 47.71%. Consequently, our PCA captures more than 75% of the total variance. The optimal index obtained is given by the following expression:

\[
\text{CompetitionIndex} = 0.404 \times HHI + 0.487 \times CR5 + 0.314 \times Lerner + 0.185 \times Margin \quad (4)
\]

In the figure 3, we report the mean of this competition index for the EU countries over three sub-periods. The first spreads over 1999-2002 and the two following over respectively 2003-2007 and 2008-2011.

Figure 3: Evolution of banking competition index in UE

As can be noted on the figure Germany, France, Ireland for instance are much more competitive according to our index than Portugal, Belgium or Finland for instance. Globally the competition index by country is stable over the time. However there are some exceptions. Thus, it appears that the competition pressure has highly decline in the UK since 1999.

Bank business model

Even more than banking competition, the 2008 financial crisis has questioned about the implication of universal, i.e. the combination of commercial and investment banking activities into a same legal banking structure, and international banks in its instigation. Beside whereas since the 1970s and up to the crisis, diversification of business lines appeared benefit for the economy, which justified the gradual end of banking activity re-
strictions, the crisis marked a reversal of this paradigm. Structural reform initiatives, as the Volcker rule for the US, the Vickers commission report in the UK, and the Liikanen report in EU, have been undertaken (implemented) to re-regulate the financial sector. The aim of these proposals is to refocus banks on important activities for real economy or at least isolate the latter from the risks of non-bank activities.

An important number of contributions seems to justify these proposals. From a theoretical point of view, Wagner (2010) shows that their is an individual benefit of income diversification for banks, but in the same time a negative impact for the systemic stability. The first argument refers to the benefits of the risk diversification portfolio (see, Boyd et al., 1981; Kwan, 1998). The second effect is due to the fact that universal banking would lead to an increase of the correlation between banks, and consequently the system would suffer of lack of diversity (see, Haldane, 2010). As suggested by Wagner (2010) there would be an optimal level of banking diversification. From an empirical view point a way to proxy universal banking is to observe bank income and especially the part of non interest income in total income (see, Stiroh, 2004). Lepetit et al. (2008) show for European banking industry over the period 1997-2002 that banks whose the incomes are more based on trading, commission and fee activities present higher risks than banks which mainly supply loans. This finding is corroborated by Stiroh (2004) who underlines that although, there are diversification benefits, these gains are offset by the higher exposure to non-interest activities, which are much more volatile without being more profitable than loans activities. DeYoung and Roland (2001) explain that this increase of volatility and risk is in part due to the fact that regulatory capital requirement is less restrictive for non interest rate activities that can lead to a higher financial leverage. Another way to confirm this negative effect of diversification is to observe market valuation of financial conglomerate versus market valuation of focused banks. Laeven and Levine (2007) find that there is a diversification discount, that is that market valuation is lower for conglomerate banks.

Since we want to study the influence of universal banking on the macroeconomic volatility of an economy, we are much more interested to the systemic effect of non-interest income. De Jonghe (2010) shows that systemic risk exposures, measured by the tail beta, that is the scale of a decline of bank’s stock price conditional on a crash in a banking index, is higher for diversified banks.

In the light of the above literature, we expect that an activity shock will have more impact on credit supply in the countries whose banks are more diversified. As usual in the literature, we choose the non interest income provided by World Bank database to take in consideration the specificity of bank business model in the EU. For robustness,
we also consider another indicator: the loans to assets ratio.\textsuperscript{8} The latter indicates the focus of banks on their core activity and the importance of other-bank activities.

Figure 4: Evolution of non-interest income ratio in UE

Figure 4 displays the evolution of bank business model. We can make some comments. First, it appears there is not convergence process toward a single business model in EU despite single market laws and directives for banking services. Banking markets appear always very disparate. Thus, the UK, France and Germany have financial systems much more based on non interest income. This can be explained by the presence in these three countries of huge international conglomerate groups, which are leaders on some segments in line with financial markets. At the bottom of the ranking, we find Greece, Portugal or Spain. The lack of important international conglomerates in these countries with the exception of Banco Santander in Spain, is an explanation; the structure of these economies, their stage of economic development and also the weakly of the competitive pressure in these markets are other explanations. Last, we note that some countries have known important evolution. On the one hand, we observe an evolution of non-interest income these latter years in Finland and the Netherlands. On the other hand, we also find an important decline of non-interest income in France since the financial crisis. This can be seen as a strategic refocusing of french financial system on traditional banking activities or/and a decrease of incomes from fee, trading and commission following the financial crisis.

\textsuperscript{8}Built from ECB data.
Bank-based vs. market based financial system

The literature questioning about the macroeconomic effects of bank-based and market-based financial systems often compares in EU, Germany and the UK. Germany representing a bank-based financial system and the UK a market-based financial system. This financial system heterogeneity in EU can be explained by divergences of levels of development, sectoral composition of the economic activity and institutional distinctions (Gambacorta et al., 2014). Thus, it appears that market-based systems are much more widespread in countries with high GDP per capita. This is also the case in economies based on services (in opposition to economies based on industry) since the assets for tertiary activities are less tangible and consequently more difficult to collateralize for banks. Without any doubt, the average size of firm also plays. Indeed SME firms do not easily issue debt securities because of fixed costs of issuance. Last, common laws in the opposite of French civil laws (Porta et al., 1998) would promote direct finance since they offer more rights to direct investors.

Beyond to explain the financial system heterogeneity, the literature has tented to find “which is better” (Levine, 2002) between bank-based and market-based financial systems. To answer to this question one part of the literature has focused on the effects on the long-run growth. For instance Levine (2002) finds that financial system types are not relevance for growth. Another stream of the literature, closer to the scope of our study, has studied whether financial orientation of an economy influences the macroeconomic volatility. Bolton et al. (2013) consider that bank-based systems are characterized by relationship banks, and they show that in this case banks cushion normal economic downturns more than transaction holder financial systems. This positive effect would be due a higher ability to screen and monitor borrowers in bank-based financial system. Thank to that banks get soft information that allows to manage more easily cross-sectional and intertemporal risks. However as noted by Gambacorta et al. (2014) “financial crisis can impair banks’ shock-absorbing capacity”. Obviously, if the banking system experiences financial difficulties related to the financial crisis, the ability to smooth cycle disappears and market-based financial systems become more profitable.

To analyze the effect of financial structures on credit cyclicity one needs a measure of financial structure. Unfortunately, there is no consensus about the definition of bank-based or market based financial systems in the literature. Often in the empirical research, the ratio of stock market capitalization to credit is used as proxy. However for our part, we only use this indicator for robustness check since we prefer the bank credit to private sector over total credit to private sector ratio. Higher is the ratio, more bank-based the
financial system is.
One again the figure 5 highlights the important heterogeneity of financial structure in EU. As expected, German financial system is among the most bank-based systems in Europe. From that standpoint, Germany and Greece are very close. Other economies as Italy, Spain, Denmark or Austria can also be considered as bank-based financial systems since bank credit represents in these countries at least 60% of total credit to the private sector. In the opposite France, Belgium, the UK, the Netherlands, Sweden and Finland are rather market-based systems. Surprisingly, because it is often cited as an example of market-based financial system, the UK does not appear among the top bank-based in Europe. It appears that its bond market is relatively small in comparison with Belgium for instance which confirms ESRB (2014) findings.

Figure 5: Scale of bank-based financial system in EU

Capital

It is widely accepted that capital requirements, especially such as design in Basel II, is a source of procyclicality. This phenomenon has two well-known sources. First, during a recession, banks experience more financial losses on their loans and on their other activities, that weakens bank equity capital and the ability of banks to take new risks and supply new credits that accentuate the cycle.\textsuperscript{9} This first aspect is not specific to banking industry and Basel II. Beside some empirical investigations show that the credit experienced at the beginning of the 90s in the US is in part due to the introduction of\textsuperscript{9}This is mainly due to the fact that raising new capital in downturn time is difficult and costly because their are frictions and imperfect capital markets in the “real world”.

\textsuperscript{9}
The second source of procyclicality is exclusively the result of Basel II capital requirement rules. Under Basel II, the higher the credit risk of an asset, the higher the capital that a bank must to hold is. That means that the amount of capital is risk-weighted. This risk-weighted capital regulation leads to a co-movement of bank capital requirement and the business cycle independently of effective capital losses since risk evaluation by internal models or rating agencies of a given asset fluctuates over the time and increases in bad time. Consequently, as already indicated, bank capital supports and strengthens the cycle: banks hold less capital and over lend at the top of the business cycle, when inobservable systemic risk is the most important and they must to have more capital and reduce loans in downturn whereas the turnaround of business cycle requires credit expansion and not credit crunch. There is an important body of literature investigating this procyclicality of the capital regulation. Chen (2001) explains the procyclicality of banks by the fact that bank capital serves as collateral. Thus a change in a level of bank capital due to loan losses, reduces bank ability to lend since the value of its collateral makes difficult to find alternative sources of funding. Kashyap and Stein (2004) confirm using simulation over the 1998-2002 period that Basel II capital requirements have increased the cyclicality of capital charges that for us means more credit fluctuations. Zicchino (2006) examines the impact of macroeconomic conditions on bank capital and loans. The author points out that risk-weighted capital leads banks to hold less capital during boom period, i.e we will observe an increase of leverage. In this case, banks become more vulnerable to unexpected negative shocks and it will be more likely for bank capital to be binding under Basel II than Basel I. Consequently, the author recommends that banks keep a capital buffer during expansion period. In this way, the likelihood for bank capital to be binding will be reduced as well as the likelihood of credit rationing. Heid (2007) confirms that capital requirements under Basel II reinforce lending cycle and points out that capital buffer that bank optimally hold under capital II reduces volatility of capital and of the loan supply. Following this short literature review, we expect that risk-weighted capital reduces the credit cyclicality. Indeed since all EU countries have the same minimum regulatory capital requirements, the higher the risk weighted capital hold is, the higher is the capital buffer.

\[ \text{see, Bernanke et al. (1991).} \]
\[ \text{Despite all Basel II is a best regulation framework than the “one size fit all” approach of Basel I since it links capital to risk and not to a category of loans. Repullo and Suarez (2013) find that it reduces bank’s probabilities of failure. Thank to that, and despite the fact that credit supply is significant more procyclical under Basel II, the authors conclude that Basel II dominates Basel I.} \]
\[ \text{That means that the denominator of the capital ratio requirement increases that rises the need of capital.} \]
\[ \text{See for a very complete review, Drumond (2009).} \]
In figure 6, we display the evolution over three sub-periods of the risk-weighted capital held by the different EU financial systems. First, it can be argue that risk-weighted capital is not structural. It is true that there is in some case important evolution especially since 2008. However it also appears that risk-aversion that reflects capital buffer is a structural features of the different financial systems in EU.

Figure 6: Evolution of risk weighted regulatory capital in UE

4 Data and Methodology

4.1 Data

Our empirical analysis spreads over 2000q1-2012q4 and includes the EU’s fifteen member economies with the exception of Luxembourg \(^{14}\) (i.e, our data set comprises the 14 following countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, United Kingdom). Our sample is relatively short since it includes only 56 quarters of observations, however panel structure of our data set allows to get efficient statistical inference. For the analysis of credit cyclicalty in EU, we retain 4 quarterly macroeconomic indicators as endogenous variables in our baseline P-VAR model. Our 4 main variables are real GDP, the consumer price index (CPI), the nominal bank credit stock to private sector and the nominal short-term interest rate. An alternative specification of VAR model also includes the stock price index. Table 6 in appendices presents an overview of the macroeconomic variables used.

\(^{14}\)The financial singularity of Luxembourg could bias results and it is common to exclude Luxembourg to EU or Eurozone empirical analysis.
in our empirical analysis and their sources. Except for the short-term interest rate all
data are seasonally adjusted. Furthermore real GDP, nominal credit and stock price
index are log-transformed.
Since we are interested in economic fluctuations, we do not consider previous macroe-
onomic indicators in level or in first-difference but in their HP-filtered version in order
to keep only the cyclical component of these variables and to exclude the trend. Thus
our P-VAR input variables define the gap in percentage between the trend value and the
observed value of the different macroeconomic indicators used.

4.2 Interacted Panel-Var methodology

To examine the relationship between business and bank credit cycles for a panel of
countries a standard approach might be to use a panel-VAR methodology. However the
panel-VAR methodology does not allow to take explicitly into account the underlying
heterogeneity. Indeed this approach captured heterogeneity only by demeaning the data,
that is by adding a fixed effects; that means we consider that the factors being the cause
of heterogeneity are not observable. Also in this case, slope coefficients remain homo-
geneous between the countries that can cause heterogeneity bias (Pesaran and Smith,
1995). Since the aim of our analysis is to model this heterogeneity and especially take
in evidence the country structural characteristics that explain the latter, the standard
panel-VAR methodology has to be updated.
Loayza and Raddatz (2007), Sá et al. (2014), Towbin and Weber (2013) or Georgiadis
(2014) develop panel-VAR frameworks where the autoregressive coefficients are linked to
country specific structural characteristics. Towbin and Weber (2013) call a such model
Interacted Panel VAR (IPVAR)\(^\text{15}\) since they interact the structural factors considering
as exogenous variables with the endogenous variables of the VAR while Georgiadis
(2014) framework is referred as Panel Conditionally Homogeneous VAR model since the
response of a shock is in such model conditional to structural characteristics.
We refer to these contributions and our baseline model has the following reduced form:

\[
Y_{i,t} = \sum_{k=1}^{L} A(Z_{i,t})_{i,t,k} Y_{i,t-k} + u_{i,t} \quad u_{i,t} \sim N(0, \Sigma) \quad (5)
\]

where \(y_{i,t}\) is a \(q+1\) vector of endogenous variables, \(A_{i,k}\) is the coefficient matrix of the VAR
which is function of \(Z_{i,t}\), the country specific and time variant structural characteristics

\(^{15}\)We are very grateful to Sebastian Weber for providing us available their matlab code for interacted
Panel VAR procedure.
and \( u_{i,t} \) a normally distributed error term with \( \Sigma \) a \( q \times q \) covariance matrix. Indices \( t \) and \( i \) refer respectively to countries and quarters.

For greater clarity, we present the model in its so-called recursive form:

\[
\begin{pmatrix}
1 & 0 & 0 & 0 \\
a_{21}^{i,t} & 1 & 0 & 0 \\
a_{31}^{i,t} & a_{32}^{i,t} & 1 & 0 \\
a_{41}^{i,t} & a_{42}^{i,t} & a_{43}^{i,t} & 1
\end{pmatrix}
\begin{pmatrix}
Infcycle \\
GDPcycle \\
BLcycle \\
icycle
\end{pmatrix}
= \mu_i + \sum_{l=1}^{L} \begin{pmatrix}
\alpha_{11}^{i,t} & \alpha_{21}^{i,t} & \alpha_{31}^{i,t} & \alpha_{41}^{i,t} \\
\alpha_{12}^{i,t} & \alpha_{22}^{i,t} & \alpha_{32}^{i,t} & \alpha_{42}^{i,t} \\
\alpha_{13}^{i,t} & \alpha_{23}^{i,t} & \alpha_{33}^{i,t} & \alpha_{43}^{i,t} \\
\alpha_{14}^{i,t} & \alpha_{24}^{i,t} & \alpha_{34}^{i,t} & \alpha_{44}^{i,t}
\end{pmatrix}
\begin{pmatrix}
\epsilon_{i,t}
\end{pmatrix}
\tag{6}
\]

The structural parameters \( \alpha_{i,t} \) distinguish the traditional panel-VAR from our framework and allow to analyze how the response of bank credit cycle to business cycle shocks varies according to some economic characteristics and their relative evolution. Thus for this purpose these coefficients have the following form:

\[
\alpha_{i,t} = \beta_{i,t} + \eta_i Z_{i,t}
\tag{7}
\]

where \( \beta_{i,t} \) and \( \eta_i \) are two vectors of coefficients and \( Z_{i,t} \) a matrix of variables underlying individual (country) heterogeneity. Therefore, the structural parameters \( \alpha_{i,t} \) vary over the time and across countries thank to the exogenous structural characteristics. However note that the coefficient are not country specific. As said by Georgiadis (2014), the coefficients remain “conditionally homogeneous”. Indeed, if the structural characteristics are the same between the countries, the slope coefficients will be also the same.

To obtain impulse response functions (IRF), after estimations (equation by equation) by OLS of the reduced form of the VAR model, we compute the Choleski decomposition of the variance matrix of the residuals. In this way we make the residuals orthogonal.\(^{16}\) Importantly note that we do not demean our data when we test simultaneously for all determinants. Therefore, in this case (section 5.2) we consider that the heterogeneity is fully observable. By contrast, in section 5.1 we consider fixed effects.\(^ {17} \)

For Choleski decomposition we choose the following ordering: inflation, GDP, bank credit and short-term interest rate. In this way GDP cycle responds to shocks in credit cycle only with lags and the contemporaneous response remains zero.

\(^{16}\text{This procedure is the same as transforming the system in a recursive VAR (see equation (6)).}\)

\(^{17}\text{By using OLS in dynamic model parameter estimates can be biased, but this bias falls as the length of the sample increases (Nickell, 1981). In our case we consider that the time is not really small and that OLS estimates are consistent. Monte Carlo evidence in Judson and Owen (1999) suggest that the magnitude of the bias is small in a sample of the size used here.}\)
The ordering of inflation, GDP in a first block and financial variables in a second block is standard in the macroeconomic literature using VAR methodology and allows financial variables to respond immediately to real shocks. By contrast, the relative ordering of financial variables is subject to some discussions. In our baseline model we order bank credit cycle before short-term interest rate. Thus our triangular identification structure allows bank credit cycle to react only with lags to short-term interest cycle as Bouvatier et al. (2012) for instance. As shown among others by Leroy and Lucotte (2014) interest rate pass-through is sluggish in the short-run that justifies the ordering of policy rate after bank credit.

Note also that the confidence bands for the impulse response functions were computed based on bootstrap replicated 500 times. Since we report 95% confidence bands, the lower band is the 2.5th percentile and the higher band the 97.5th percentile of the 500 bootstrapped IRF. 18

As common in VAR model, we cannot interpret the coefficients of interaction terms. Therefore we follow Saborowski and Weber (2013) and compare IRF of bank credit to a shock of output, at 20th and 80th percentiles of the distribution of the exogenous considered determinants. In other words, we compare the effect of monetary policy shocks for both low and high levels of the exogenous variables.

5 Results

Using the specification of the panel-VAR described above, we study the transmission of business cycle shocks to the credit cycle. Our a priori is that procyclicality is a source of instability, and that some factors related to the credit supply side can stabilize the credit. In this section we proceed in two steps. In the first step, we analyze the homogeneous effect (unconditional effect) of a business cycle shock to the credit cycle and underline the feedback effects of credit shocks to economic activity ever in the case of an unconditional analysis. Second, we estimate our panel-VAR with interaction terms and present impulse response functions conditional to our determinants. In this way we highlight the effects of the different indicators considered on the procyclicality of the financial system.

18 For robustness purpose, we have checked our IRF results for different orderings and for a more conservative ordering, where bank credit is ordered last. However we get comparable results, see section robustness.
5.1 Unconditionnal relationships between business and credit cycles

In this subsection we consider that $\eta$ in equation 7 is null. Therefore the panel-VAR in 6 does not comprise indicators of financial structures and parameters are homogeneous. We take into account the heterogeneity by demean the endogenous variables.

Figure 1a displays the median of the bootstrapped impulse response function of credit cycle for activity cycle innovations, (here for a 1 percent increase of output gap determined by HP-filter) with the two standard-error confidence bands, computed by bootstrapping (500 draws). As can be seen credit cycle responds positively and significantly to business cycle. The positive effect of GDP on credit is an expected result and is in line with many other previous findings. More interestingly, the cumulative effect is superior to 1. In average in European Union an output gap on 1% leads to an credit gap superior to 2%. Since some contributions focus on the growth of credit and GDP to analysis procyclicality, we also report impulse response function from our unconditional model with macroeconomic variables no detrended but just first-differentiated. Figure 1b confirms that in average bank credit is highly procyclical in European Union. In addition, an activity shock in this case seems to have a permanent effect on bank credit. The main explanation is that the credit response to an activity shock has feedback effects on activity.

Our standpoint is that these average effects mask heterogeneity, that we study in the next subsection. Before that, we analyze the feedback effects of bank credit on activity. Our aim is indeed to show that procyclicality is costly since a negative bank credit shock deteriorates the business cycle. The underlying idea is that a deterioration of credit market conditions - for instance a decrease of the volume of available credit - are not a passive reflection of the real economy, but is a factor participating to the weakening of the real economy. This view is of course today mainstream and has been documented by many contributions (see, Bernanke (1983) for the effects of bank failure on aggregate output during the Great Depression).

To highlight these feedback effects, we report impulse response of business cycle for a credit shock from our homogeneous panel-VAR model. After a such shock, the output gap starts to increase for about 3 quarters, before to recovering entirely after 2 years. By contrast the credit cycle following an output shock has a protracted effect since it increases for 5 quarters and is close to zero after 4 years. In economic terms, these feedback effects of banking sphere to real sphere, imply that the instability of the financial system - proxied by procyclicality - has adverse effects on the aggregate output.

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19 Cumulative impulse responses not reported but available upon request.
Figure 7: Average Impulse Response Functions of Credit to a shock of GDP

Note: The figure shows impulse responses of credit cycle to a one percentage point increase of output cycle. The figure at the top correspond the The solid lines correspond to the median (50th) impulse response. The two dotted lines represent the 5% error bands (two standard deviations) generated by bootstrap.

Figure 8: Average Impulse Response Functions of GDP to a shock of Credit

Note: The figure shows impulse responses of output cycle to a one percentage point increase of credit cycle. The solid lines correspond to the median (50th) impulse response. The two dotted lines represent the 5% error bands (two standard deviations) generated by bootstrap.
5.2 Modeling the heterogeneity: What is the influence of credit supply indicators?

Our previous specifications consider homogeneous coefficients and consequently our results focus on the average response of credit cycle to a business cycle shock. Now, we reduce the constraint in our model by allowing coefficients to be heterogeneous according to the financial supply indicators, which is permitted thanks to the inclusion of interaction terms in our previous panel-VAR. At this point the question that we address is therefore what factors could explain differences in term of procyclicality?

Procyclicality and bank structures

Figure 9 depicts the impulse responses of bank credit cycle to an output shock, based on the panel-VAR model estimated (equation 6) with \( Z_{i,t} \) including only one financial structure indicator at the time.

First of all, we observe that an unanticipated increase of one percent of the output gap causes a more important response of bank credit in highly competitive banking market. As can be shown on the graph furthest to the right in Figure 9, the difference is significantly different to zero at the 5% significance level and the economic effect appears sizable. Thus, banking competition allows to smooth cycles. There are two possible explanations, not necessarily opposite but rather complementary, for this results:

- first, bank competition would allow to solve more easily asymmetric information problems between borrowers and lenders. In this case, banking competition should promote screening, enforcement of selecting borrowers, monitoring and/or engaging in long-term relationships. This is consistent with Boot (2000) model, where competition increases the part of relationship lending. Indeed, the relationship orientation would allow to partially insulate banks from pure price competition. Furthermore, since our banking competition proxy includes two measurements of banking concentration,\(^{20}\) the stabilizing effects of competition could be the results of the level of concentration. Low level of concentration could indicate a more relationship lending system since that would imply more of regional, cooperative or saving banks whose business models are more focused on relationship lending.

- second, bank competition could reduce risk-taking incentives as theoretically shown by Nicoló et al. (2006) and empirically found by Schaeck and Cihak (2012) and Uhde and Heimeshoff (2009) for the EU.

When we test for the impact of business model, the impulse response functions of bank credit to an activity shock show that a high level of non-interest income ratio reduces

\(^{20}\)Our bank competition index is partially based on the SCP paradigm.
significantly the volatility of bank credit. A priori no argument can support that non interest income ratio would favor bank-relationship. The only way by which non interest income ratio could improve the resolution of asymmetric information problems is by the improvement of screening and monitoring techniques. Since non interest income ratio could proxy the level of sophistication of a banking system, screening and monitoring techniques could be more efficient in such systems. Nevertheless the argument remains weak. A more valuable explanation would be that non-interest income would allow diversification benefits.

Our third result is that bank-based systems are less volatile than market-based systems. However, we note that the statistical significance is weak as well as the economic effect compared to the two previous results. This positive effect can be explained by a higher ability to screen and monitor borrowers in bank-based financial systems, which allows to manage more easily cross-sectional and intertemporal risks. If we consider that capital market competition is lower in bank-based systems, our findings confirm results of Boot (2000) model. Indeed, beyond to show that banking competition can increase relationship lending, the model also show that capital market competition reduces relationship lending.

Last result, we observe in the fourth part of figure 9, that risk-weighted capital ratio is a factor that highly reduces the procyclicality of bank credit. Since minimum capital requirements are the same across EU countries, different levels of risk-weighted capital ratio indicate different levels of capital buffer. Here, we note that capital buffer allows to smooth procyclicality of banking system. Undoubtedly, this result justifies the implementation of a counter-cyclical capital buffer in Basel III.
Controlling for correlations between the determinants

In this subsection we control for correlation between the different indicators. Indeed there are several empirical evidences as well theoretical contributions that highlight correlations between the factors considered. For instance, Schaeck and Cihak (2012) show that banking competition leads bank to hold more capital.

We report IRF results in figure 11. Despite the fact that the model is highly parameters, since we consider simultaneously 4 interaction terms, error bands remain reasonable. We report two types of results: results obtained from specifications with and without fixed effects.

Globally, the results in figures 10 and 11 confirm our previous findings with the exception of the indicator of bank business model. Thus, we find that competition (low concentration) reduces the procyclicality of the banking system. Well capitalized and bank based systems have a similar effect. By contrast, the non interest income ratio appears to increase the response of bank credit to an activity shock. This is in opposite with our previous findings. When we model explicitly the other sources of heterogeneity and consider their median value, we find that the non interest income ratio increases the instability. Indeed, the procyclicality is higher when the non interest income ratio is at its 80% percentile value. Results seem more coherent with our other findings. This means that the focus of business models on loans reduces procyclicality. Thus, banking systems where universal and international banks occupy a preponderant place have a credit sector more unstable. There is no gain in term of smoothing to have such systems. Results from figures 10 and 11 are the same. From this observation, we conclude that our 4 interaction terms making the response conditionally homogeneous, model relatively well the heterogeneity of our panel. Indeed, taking into account a residual unobservable heterogeneity by demean the data does not lead to a modification of our conclusions.
Figure 9: Impulse Response Functions of Credit following a shock of GDP: Baseline model

(a) Bank competition

(b) Bank business model

(c) Nature of the financial system

(d) Capital

Note: The figure shows impulse responses of Credit to a one percentage point increase in output cycle under the 20th (“low”) and 80th (“high”) percentile level of the interaction variable. The figures on the right represent the difference between the two. The solid lines correspond to the median (50th) impulse response. The two dotted lines represent the 5% error bands (two standard deviations) generated by bootstrap.
6 Robustness checks

6.1 Usual robustness checks

To examine the robustness of the results presented above, we estimate different panel-VAR specifications. We consider 4 other specifications. First, we check our results for a different lag-structure. Especially, we estimate panel-VAR with one supplementary lag (3 quarters) and find that the results are very close. Second, as common in VAR model, we check the robustness of our findings using different ordering of the variables. In our baseline model, bank credit is ordered before the short-term rate when we perform the Cholesky decomposition. Our theoretical justification is that the interest rate pass-through is sluggish. Consequently the supply and demand of bank credit react only with a lag to innovations in short-term rate. Our choice is consistent with Assenmacher-Wesche and Gerlach (2008) and Bouvatier et al. (2012). Nevertheless, the choice remains arbitrary and we can assume that Central Banks do not react to current amount of bank credit. Therefore, we switch the ordering of credit and policy rate. Results in figure 14 appear to be highly consistent.21 The other ordering choices appears standard and consensual in the literature (see Christiano et al., 1999). Third, we exclude from our sample Greece (figure 15) and find that impulse response functions are very similar to our baseline model. Last, we retain different proxys for three of our indicators. We proxy bank competition by an equal weight index, business model by the loans over assets ratio and nature of the financial by the stock market over credit ratio. In all the cases results remain comparable (see figure 17).

6.2 Controlling for credit demand side

A potential caveat of our empirical strategy is that we focus exclusively on the supply side of the credit market. Nevertheless, some factors related to credit demand side have certainly an impact on the procyclicality of the financial system. In this subsection we check whether these factors call into question our previous results.

The first question to ask is what demand factors might play on credit procyclicality? According to the theoretical arguments raised previously in this paper, the structural demand factors have to act on asymmetric information to influence credit procyclicality. We consider that the sectoral composition of an economy can influence the level of asymmetric information problems and the bank ability to resolve these problems. We retain two different indicators related to the firm structural composition of an economy:

---

21 That means that correlation between credit and policy rate innovations are small
Figure 10: Impulse Response Functions of Credit following a shock of GDP: Controlling correlation between the 4 indicators (with fixed effects)

Note: The figure shows impulse responses of Credit to a one percentage point increase in output cycle under the 20\textsuperscript{th} ("low") and 80\textsuperscript{th} ("high") percentile level of the interaction variable. The figures on the right represent the difference between the two. The solid lines correspond to the median (50\textsuperscript{th}) impulse response. The two dotted lines represent the 5\% error bands (two standard deviations) generated by bootstrap.
Figure 11: Impulse Response Functions of Credit following a shock of GDP: Controlling correlation between the 4 indicators (without fixed effects)

(a) Bank competition

(b) Bank business model

(c) Nature of the financial system

(d) Capital

Note: The figure shows impulse responses of Credit to a one percentage point increase in output cycle under the 20th (“low”) and 80th (“high”) percentile level of the interaction variable. The figures on the right represent the difference between the two. The solid lines correspond to the median (50th) impulse response. The two dotted lines represent the 5% error bands (two standard deviations) generated by bootstrap.
the share of output by industries producing durable goods and the share of SME in the productive system.

To check our previous results we consider these indicators one by one with one financial structure indicator at each time. As can be shown in figure ??, our findings remain consistent.

6.3 Counterfactual analysis

In response to the financial crisis, the European Commission has pursued a number of initiatives to create a safer and sounder financial sector for the single market. These initiatives has led the foundation of a Banking Union which includes the establishment of a Single Supervisory Mechanism and of a Single Resolution Mechanism, but also of the improvement of bank prudential requirement in all European Union Member States. This harmonization of financial rules in Europe should also lead to a convergence of financial structures, such as we have defined them previously in this article. This is particularly likely since European Commission is pursuing project to harmonize financial structure. A concrete example is the Liikanem report. The question can be posed: what model of financial structure should Europe to favor and generalize to the entire area to insure a sounder banking sector, i.e here to insure less procyclicality of banking credit?

In this part, we propose to make a counterfactual study where we compare two credible models for financial structures in EU for the future.

We conduct our counterfactual analysis in two-steps. First of all from the four indicators of financial structure used in this study, we try to distinguish and isolate a limited number of financial structure models in Europe. In order to do this, we make a cluster analysis. Cluster analysis meets our expectations since it allows to group countries such that the banking structures of countries of a same group are more similar than those in other clusters. The fact that different kinds of financial structure exist, allows then to compare the procyclicality of bank credit on the basis of average characteristics of financial structures of the different groups.

There are several ways to make clusters analysis. The most straightforward method is hierarchical clustering, which can be either agglomerative or divisive. In our case, we retain Hierarchical Agglomerative Clustering (HAC). Agglomerative techniques consist to start with \( n \) groups, with \( n \) equal to the number of countries and reducing step by step the number of group by merging different clusters according to their dissimilarity. The implementation of this strategy raises the question of the way to measure distance, i.e dissimilarity, and the way to merge clusters at each step. To measure the initial dis-
tance between the financial structures of our sample of European countries and to build our proximity matrix, we use squared Euclidean distance between our four variables of financial structure. We retain only the last observations of financial structure variables since our motivation is to define the actual sounder financial system. Furthermore, the variables have been standardized to avoid that the variables with the larger scale have a greater impact on the determination of clusters. To combine clusters at each stage and obtain homogeneous groups, we use Ward’s algorithm, which minimizes the increase in variance for the cluster being merged.

In order to have a visual representation of the results of HAC analysis we report the dendogram (figure 12), which displays the distance at which clusters are combined. Furthermore to have comprehensive and general conclusions, we retain three clusters.
- cluster 1: United-Kingdom, Denmark, the Netherlands, Finland, Ireland and Belgium.
- cluster 2: Greece and Portugal.
- cluster 3: Germany, Austria, Spain, Sweden, France and Italy.

Descriptive statistics of the variables by cluster (table 2) allow to explain what disperses banking system in three groups. First of all, cluster 2 corresponds to a group of countries severely affected by the crisis, which is reflected by the low level of capital. Moreover, we also note that Greece and Portugal are significantly less competitive, more bank-based and have less diversified and sophisticated banks than the European average. Since this kind of banking structure is very singular and does not constitute a model to be followed, we do not consider this cluster for our counterfactual analysis. In our view, the two other clusters are much more interesting since they are two credible and distinct options for the future of financial structures in Europe. Thus, cluster 1 gathers countries whose the banking systems are in average concentrated, relatively well capitalized and market based. As regards the cluster 2, it comprises banking systems weakly concentrated and highly bank-based. The distinction of these two clusters is particularly interesting for counterfactual analysis since the two models could have different implications in term of procyclicality. Even if the credit procyclicality cannot - and must not - be the only criteria to determine which system is the best because that overlooks the question of allocative efficiency for instance, we consider that financial structural policies have to take this point into consideration.

As can be shown on figure 13, in average in cluster 3, the response of credit to an output shock is lower than in cluster 1.
Table 2: Cluster summary statistics

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Bank competition</th>
<th>Capital</th>
<th>Bank credit over credit</th>
<th>Business model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster 1</td>
<td>1.39</td>
<td>15.7</td>
<td>49.14</td>
<td>34.07</td>
</tr>
<tr>
<td>Cluster 2</td>
<td>2.63</td>
<td>9.7</td>
<td>75.58</td>
<td>21.32</td>
</tr>
<tr>
<td>Cluster 3</td>
<td>-1.18</td>
<td>13.71</td>
<td>65.08</td>
<td>38.94</td>
</tr>
<tr>
<td>Total</td>
<td>0.46</td>
<td>13.99</td>
<td>59.75</td>
<td>34.34</td>
</tr>
</tbody>
</table>
6.4 The financial accelerator à la Kiyotaki and Moore

Kiyotaki and Moore (1997) model the financial accelerator in a different fashion than Bernanke and Gertler (1989). They point out that asymmetric information problems constraint banks to require collateral. Consequently, the ability to raise external funds is dependent to the value of collateral. More the value of collateral is high, more important the ability of bank credit is. Apart this specificity, the financial accelerator mechanism is the same as Bernanke and Gertler (1989). The reduction of firms’ net worth, caused by a decrease of the value of collateral, leads to a reduction of the aggregate level of investment and production. Kiyotaki and Moore (1997) model allows to explain unconventional policy measures implemented by monetary and fiscal policy authorities, especially in the US, where the FED has directly supported real estate and financial markets.

In order to take into consideration this reality, we first add in our baseline panel-VAR model a fifth endogenous variable: the stock market price. As shown in 18, the responses of credit to GDP shock remain dependent of the 4 factors underlined above. From this specification, we also test the response of credit to an unexpected evolution of stock market prices. We observe that bank credit reacts more to market prices (our proxy of the value of collateral) in poorly competitive markets, bank system more focused on loans and market-based financial systems. Capital ratio has no effects.

7 Conclusion

This paper empirically analyzes the effects of financial structures of European union countries on the credit procyclicality over the time period from 2000 to 2012. Our study contributes to the debate on the influence of financial structures on the financial fragility as well as on the economic instability. Indeed in our view and consistent to financial accelerator theory credit procyclicality can be consider as a measure of instability since the credit procyclicality amplifies the cycles and leads to credit boom and bust more pronounced. Therefore credit procyclicality leads to a more unstable economy.

Our findings suggest several conclusions.

- The co-movement between credit and output cycles are very divergent in EU. This result tends to show cross-country difference of intensity of credit procyclicality.

- Financial accelerator theory mechanisms are verified in EU. In average in UE the credit is procyclical, which is an evidence of the existence of an propagation mechanism. Furthermore unexpected shock in credit impact output cycle (amplification
mechanism). This result confirms the relevance of credit procyclicality as a measure of instability and offers theoretical foundation to explain heterogenous credit procyclicality.

- This paper highlights that financial structures matter for credit procyclicality and for instability. Competition, bank based, well capitalized and focus financial systems reduce procyclicality of the credit and insure more stability. We explain these findings by the fact that such systems would be more able to mitigate asymmetry information problems and alleviate incentives to risk-taking.
Appendix

An alternative to test the hypothesis that the credit procyclicality is function of financial structures, consists to use panel fixed effects regressions. For that we estimate the following model:

\[ Y_{i,t} = \alpha_0 + \beta_1 X_{i,t-1} + \sum (HP-\text{filtered}\beta_k X_{i,t-1} \ast Z_{i,t-4}) + \sum \beta_{k+1} \text{Determinant}_{i,t-4} + \varepsilon_{i,t} \]  

(8)

where \( Y_{i,t} \) refers to the HP-filtered version of bank credit in country \( i \) and at time \( t \), \( X_{i,t-1} \) the HP-filtered version of activity. The vector \( Z_{i,t-4} \) includes the different indicators of financial structures. \( \varepsilon_{i,t} \) is the error term and \( \alpha_0 \) and the \( \beta \) denote the parameters to be estimated.

Employing a such methodology only allows to check our results. Indeed, the latter methodology suffers of some caveats. The most important is that we consider GDP cycle as an exogenous variable.

We present empirical results in table 3. Regressions (1) reports the average effect of activity cycle on credit cycle. (2), (3), (4) and (5) consider successively the effects of banking competition, bank-business model, bank-based type and capital.
Table 3: Estimation results: HP-filtered GDP and bank Credit

<table>
<thead>
<tr>
<th>Variables</th>
<th>Panel elasticity</th>
<th>Competition effects</th>
<th>Business model effects</th>
<th>Bank-based effects</th>
<th>Capital effects</th>
<th>Controlling for correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>0.697***</td>
<td>0.694***</td>
<td>-0.276</td>
<td>0.254</td>
<td>2.233***</td>
<td>-0.355</td>
</tr>
<tr>
<td>(0.047)</td>
<td>(0.049)</td>
<td>(0.203)</td>
<td>(0.275)</td>
<td>(0.386)</td>
<td>(0.535)</td>
<td></td>
</tr>
<tr>
<td>Y*Competition Index</td>
<td>0.088***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competition Index</td>
<td>-0.003</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y*Bank business model</td>
<td>1.592</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.117***</td>
</tr>
<tr>
<td></td>
<td>(0.330)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Business model</td>
<td>0.036</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.819</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y*bank based</td>
<td>0.551</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Bank based</td>
<td>0.171***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.177***</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y*Capital</td>
<td>-0.129***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.052*</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capital</td>
<td>-0.003***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.001***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.001</td>
<td>0.001</td>
<td>-0.010</td>
<td>-0.105</td>
<td>0.039***</td>
<td>-0.098</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.008)</td>
<td>(0.017)</td>
<td>(0.007)</td>
<td>(0.021)</td>
</tr>
</tbody>
</table>

Global effect of Y | 0.707*** | 0.766*** | 0.594*** | 0.630*** | 0.666*** |
|                   | (0.050) | (0.052) | (0.05) | (0.048) | (0.051) |
Adj R-squared      | 0.204  | 0.206  | 0.22   | 0.223   | 0.247    | 0.31  |
D-W-stat           | 0.335  | 0.332  | 0.33   | 0.318   | 0.344    | 0.37   |

The panel model estimated is: \( HP - filteredBankcredit_{it} = \alpha_0 + \beta_1 HP - filteredGDP_{it-1} + \sum_{t=1}^{T} \beta_t (HP - filteredGDP_{it-t} * Determinant_{t,i,t-4}) + \sum_{t=1}^{T} \beta_{\Gamma,n,alpha+1} Determinant_{t,i,t-4} + \epsilon_{i,t}. \) Standard errors reported between brackets. *, **, *** refer to statistical significance at the 10%, 5% and 1% respectively.
Table 4: Cross-country Mean, Maximum, Final and Initial responses of Credit cycle to an Output cycle shock from Individual Country Var models

<table>
<thead>
<tr>
<th>Country</th>
<th>Mean</th>
<th>Maximum</th>
<th>T=8</th>
<th>T=0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria</td>
<td>0.194</td>
<td>0.348</td>
<td>0.119</td>
<td>0.071</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.674</td>
<td>0.898</td>
<td>-0.003</td>
<td>0.563</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.615</td>
<td>0.78</td>
<td>0.664</td>
<td>0.198</td>
</tr>
<tr>
<td>Finland</td>
<td>0.438</td>
<td>0.569</td>
<td>0.326</td>
<td>0.267</td>
</tr>
<tr>
<td>France</td>
<td>0.512</td>
<td>0.63</td>
<td>0.272</td>
<td>0.248</td>
</tr>
<tr>
<td>Germany</td>
<td>0.143</td>
<td>0.201</td>
<td>0.149</td>
<td>0.073</td>
</tr>
<tr>
<td>Greece</td>
<td>1.091</td>
<td>1.531</td>
<td>1.514</td>
<td>0.292</td>
</tr>
<tr>
<td>Ireland</td>
<td>1.015</td>
<td>1.232</td>
<td>1.086</td>
<td>0.371</td>
</tr>
<tr>
<td>Italy</td>
<td>0.283</td>
<td>0.386</td>
<td>-0.051</td>
<td>0.289</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.427</td>
<td>0.628</td>
<td>-0.022</td>
<td>0.507</td>
</tr>
<tr>
<td>Spain</td>
<td>0.851</td>
<td>1.29</td>
<td>1.29</td>
<td>0.361</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.842</td>
<td>1.085</td>
<td>0.817</td>
<td>0.339</td>
</tr>
<tr>
<td>Portugal</td>
<td>0.315</td>
<td>0.42</td>
<td>0.254</td>
<td>0.084</td>
</tr>
<tr>
<td>UK</td>
<td>0.134</td>
<td>0.396</td>
<td>-0.147</td>
<td>0.396</td>
</tr>
</tbody>
</table>

The table provides the mean, the maximum, the value at T=8 and T=0 of the responses of credit cycle to an activity cycle shock from country VAR model estimates. Mean and maximum are established on the first 8 responses.

Table 5: Descriptive statistics of the financial structure indicators

<table>
<thead>
<tr>
<th>Country</th>
<th>Competition Index</th>
<th>Business model</th>
<th>Bank-based</th>
<th>Capital</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria</td>
<td>-0.86</td>
<td>0.55</td>
<td>-2.33</td>
<td>0.01</td>
</tr>
<tr>
<td>Belgium</td>
<td>2.59</td>
<td>0.69</td>
<td>1.56</td>
<td>3.95</td>
</tr>
<tr>
<td>Denmark</td>
<td>1.54</td>
<td>1.25</td>
<td>-1.14</td>
<td>3.27</td>
</tr>
<tr>
<td>Finland</td>
<td>2.45</td>
<td>0.68</td>
<td>1.3</td>
<td>4.02</td>
</tr>
<tr>
<td>France</td>
<td>-1.74</td>
<td>0.55</td>
<td>-2.66</td>
<td>-0.82</td>
</tr>
<tr>
<td>Germany</td>
<td>-3.56</td>
<td>0.48</td>
<td>-4.23</td>
<td>-2.39</td>
</tr>
<tr>
<td>Greece</td>
<td>2.96</td>
<td>1.91</td>
<td>-1.85</td>
<td>6.48</td>
</tr>
<tr>
<td>Ireland</td>
<td>-1.75</td>
<td>1.11</td>
<td>-3.27</td>
<td>0.07</td>
</tr>
<tr>
<td>Italy</td>
<td>-1.34</td>
<td>0.82</td>
<td>-2.58</td>
<td>1.01</td>
</tr>
<tr>
<td>Netherlands</td>
<td>1.91</td>
<td>0.43</td>
<td>0.86</td>
<td>2.74</td>
</tr>
<tr>
<td>Spain</td>
<td>1.94</td>
<td>1.74</td>
<td>-1.06</td>
<td>4.48</td>
</tr>
<tr>
<td>Sweden</td>
<td>-0.99</td>
<td>1.01</td>
<td>-2.53</td>
<td>1.24</td>
</tr>
<tr>
<td>Portugal</td>
<td>0.27</td>
<td>0.52</td>
<td>-0.36</td>
<td>1.8</td>
</tr>
<tr>
<td>UK</td>
<td>-0.94</td>
<td>1.61</td>
<td>-4.91</td>
<td>0.91</td>
</tr>
</tbody>
</table>

The table provides the mean, the standard deviation, the minimum and the maximum of the competition index, the non-interest income over total income ratio, the ratio of bank credit to the private sector over total credit to the private sector, and the ratio of weighted capital for our sample of country.
Figure 14: Impulse Response Functions of Credit following a shock of GDP: Different ordering

Note: The figure shows impulse responses of Credit to a one percentage point increase in output cycle under the 20th ("low") and 80th ("high") percentile level of the interaction variable. The figures on the right represent the difference between the two. The solid lines correspond to the median (50th) impulse response. The two dotted lines represent the 5% error bands (two standard deviations) generated by bootstrap.
Figure 15: Impulse Response Functions of Credit following a shock of GDP: except Greece

Note: The figure shows impulse responses of Credit to a one percentage point increase in output cycle under the 20th ("low") and 80th ("high") percentile level of the interaction variable. The figures on the right represent the difference between the two. The solid lines correspond to the median (50th) impulse response. The two dotted lines represent the 5% error bands (two standard deviations) generated by bootstrap.
Figure 16: Impulse Response Functions of Credit following a shock of GDP: 2000q1-2008q3

(a) Bank competition

(b) Bank business model

(c) Nature of the financial system

(d) Capital

Note: The figure shows impulse responses of Credit to a one percentage point increase in output cycle under the 20th (“low”) and 80th (“high”) percentile level of the interaction variable. The figures on the right represent the difference between the two. The solid lines correspond to the median (50th) impulse response. The two dotted lines represent the 5% error bands (two standard deviations) generated by bootstrap.
Figure 17: Impulse Response Functions of Credit following a shock of GDP: Alternative indicators

(a) Bank competition

(b) Bank business model

(c) Nature of financial system

(d) Capital

Note: The figure shows impulse responses of Credit to a one percentage point increase in output cycle under the 20th (“low”) and 80th (“high”) percentile level of the interaction variable. The figures on the right represent the difference between the two. The solid lines correspond to the median (50th) impulse response. The two dotted lines represent the 5% error bands (two standard deviations) generated by bootstrap.
Figure 18: Impulse Response Functions of Credit following a shock of GDP: Stock price included

(a) Bank competition

(b) Bank business model

(c) Nature of the financial system

(d) Capital

Note: The figure shows impulse responses of Credit to a one percentage point increase in output cycle under the 20th ("low") and 80th ("high") percentile level of the interaction variable. The figures on the right represent the difference between the two. The solid lines correspond to the median (50th) impulse response. The two dotted lines represent the 5% error bands (two standard deviations) generated by bootstrap.
Figure 19: Impulse Response Functions of Credit following a shock on the value of collateral

Note: The figure shows impulse responses of Credit to a one percentage point increase in output cycle under the 20\textsuperscript{th} ("low") and 80\textsuperscript{th} ("high") percentile level of the interaction variable. The figures on the right represent the difference between the two. The solid lines correspond to the median (50\textsuperscript{th}) impulse response. The two dotted lines represent the 5\% error bands (two standard deviations) generated by bootstrap.

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Table 6: Data, sources and transformations

<table>
<thead>
<tr>
<th>Definition</th>
<th>Source</th>
<th>Transformation</th>
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</thead>
<tbody>
<tr>
<td>Seasonally adjusted Real GDP</td>
<td>Eurostat</td>
<td>HP-filter on log-transformed series</td>
</tr>
<tr>
<td>Inflation</td>
<td>Eurostat</td>
<td>HP-filter</td>
</tr>
<tr>
<td>Short-term interest rate</td>
<td>Eurostat</td>
<td>HP-filter</td>
</tr>
<tr>
<td>Bank credit to the private sector</td>
<td>BIS</td>
<td>Series adjusted to break. HP-filter on seasonally adjusted and log-transformed series</td>
</tr>
<tr>
<td>Market price</td>
<td>OECD</td>
<td>HP-filter on seasonally adjusted series</td>
</tr>
<tr>
<td>Bank probability of default</td>
<td>rmi/ci</td>
<td>/</td>
</tr>
<tr>
<td>HHI</td>
<td>ECB</td>
<td>linear interpolation to match with quarterly frequency</td>
</tr>
<tr>
<td>CR5</td>
<td>ECB</td>
<td>linear interpolation to match with quarterly frequency</td>
</tr>
<tr>
<td>Lerner Index</td>
<td>World Bank (GFD)</td>
<td>linear interpolation to match with quarterly frequency</td>
</tr>
<tr>
<td>Net interest margin</td>
<td>World Bank (GFD)</td>
<td>linear interpolation to match with quarterly frequency</td>
</tr>
<tr>
<td>Non interest incomes over total incomes</td>
<td>World Bank (GFD)</td>
<td>linear interpolation to match with quarterly frequency</td>
</tr>
<tr>
<td>Risk-weighted capital ratio</td>
<td>World Bank (GFD)</td>
<td>linear interpolation to match with quarterly frequency</td>
</tr>
</tbody>
</table>

References


Haldane, A. (2010). The 100 billion question. *Speech to Institute of Regulation and Risk, Hong Kong, March.*


