Does the banking sector structure matter for credit procyclicality?*

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Abstract

The aim of this paper is to investigate whether the banking sector structure matters in explaining credit procyclicality for 17 OECD countries over the 1986-2010 period. To this end, we first provide a detailed classification of the banking system structure through the use of a hierarchical clustering methodology. Relying on the estimation of panel VAR models and accounting for potential heterogeneity between countries, we then propose a measure of credit procyclicality based on the impulse-response function of credit to a shock in GDP. Our findings show that while credit significantly responds to shocks in GDP, the structure of the banking sector is not a key factor in assessing the procyclicality of credit for OECD countries.

JEL Classification: C33, E32, E51, G21.
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1 Introduction

Addressing procyclicality in bank lending behavior has become one of the priorities for banking regulators since the 2007-2008 financial crisis, as notably illustrated by the Basel 3 proposal which merges the more advanced regulatory tools in terms of implementation (BCBS, 2010, 2011). In particular, the Basel Committee on Banking Supervision (BCBS) proposes to introduce a countercyclical capital buffer. Upward adjustments in the capital buffer would be made during periods of excessive credit growth in order to curb the credit cycle and protect the banking sector from the accumulation of financial imbalances. In addition, the BCBS advocates a change in loan loss provisioning behaviors toward more forward-looking provisioning practices. These measures seek to increase the cost of making loans in terms of capital and loan loss provisions during the upward phase of the cycle. Indeed, it is largely accepted that both borrowers and lenders are overconfident during this phase about investment projects and their ability to repay and regain their loans. Banks' over optimism about borrowers' future prospects brings about more liberal credit policies with lower credit standards requirements. Thus, some negative net present value projects are financed just to find later the impairment of the loan or the default of the borrower (Jimenez and Saurina, 2006). On the other hand, during recessions, banks face non-performing loans and specific provisions that let them to tighten further credit supply, complicating the prospects of a recovery in economic activity. These variations in lending are generally more than proportional to the changes in economic activity, suggesting that there are changes in bank loan supply that tend to accentuate the business cycle (Berger and Udell, 2004).

Regulatory tools included in the Basel 3 proposal act on banks' balance sheet to dampen the credit cycle. Some complementary measures could operate on borrowers, i.e. on credit demand (ECB, 2010). Imposing limits on loan-to-value (LTV) and/or loan-to-income (LTI) ratios in lending contracts during the upward phase of the cycle could cool down credit demand. These restrictions could concern only a specific sector or a specific type of loan depending on the sources of financial imbalances that are building-up in the economy. Furthermore, LTV and LTI ratios could be used to define capital surcharges and then also act on credit supply. For example, higher risk weights could be imposed on mortgage loans granted with higher LTV ratios when housing markets are booming. The implementation of these kinds of measures raises various challenges, including the regulatory tool calibration and the determination of trigger events. However, several countries, as for example South Korea and Hong Kong, already use LTV and LTI ratios for macroprudential regulation (Crowe et al., 2011a, 2011b).

As argued by Goodhart and Hofmann (2004), the liberalization of the financial sector has contributed to increasing the procyclicality of financial systems through the development of procyclical lending practices of banks. The historical experience tends to attach importance to this argument by showing that episodes of financial turbulence and crises have frequently been preceded by credit booming (Borio and Lowe, 2004; Detken and Smets, 2004; Adalid and Detken, 2007; Goodhart and Hofmann, 2008). However, the magnitude of credit procyclicality could differ depending on banking systems' characteristics such as size, competition or concentration. For instance, large banks could obtain a better diversification of their risks and then could be more resilient to shocks. In particular, Demsetz and Strahan (1997) show that large banks have more stable credit levels. Similarly, according to Petersen and Rajan (1995), the value of lending relationship is higher for banks with a greater market power. Banks that face a lower level of competition would have then more incentives to smooth credit access to their clients over the business cycle.[1]

Two important issues can be examined through the link between credit procyclicality and banking sector structure. First, one may investigate whether heterogeneous banking systems could expect the same stabilizing effects from regulatory tools addressing credit procyclicality. In other words, if credit is more procyclical in a specific banking sector, its regulators could have more incentives to promote an international regulation addressing procyclicality in bank lending behavior. Second, in a regulatory perspective, if the banking system structure affects how credit responds to the business cycle, regulators should also include this aspect in the design of banking regulation and not only focus on prudential measures.

In this paper, the relationship between credit procyclicality and the banking sector structure is investigated on a sample of 17 OECD countries over the 1986-2010 period. To this end, we first perform a clustering analysis to provide a classification of the banking system. We then rely on the estimation of a panel VAR (PVAR) model on cyclical components for each of the clusters and propose a measure of credit procyclicality based on the impulse-response function of credit to a shock in GDP.[2] This framework allows us to study whether credit procyclicality—i.e. the response of the credit market to a shock in GDP—depends on the structure of the banking sector.

Our paper contributes to the recent literature in several ways. First, we provide a rigorous classification of the banking system through the use of a hierarchical clustering methodology based on several indicators for our sample of OCDE countries. This allows us to specifically account for heterogeneity among countries and to base our comparison between banking systems on multiple dimensions, classifying the countries according to similarities in the structure of their banking sector. Second, relying on a PVAR framework, we add to the discussion on how to measure credit procyclicality of the banking system. Finally, we contribute to the literature on the banking system regulation by investigating the determinants that are at play in the procyclical character of credit.

The rest of the paper is organized as follows. Section 2 assesses similarities in banking sector structures through the use of a hierarchical clustering approach. Section 3 deals with the PVAR modelling and reports the estimation results for the different clusters, together with the impulse-response functions. Section 4 provides some concluding remarks.

2 Assessing similarities in banking sector structures

We consider the following sample of 17 OECD countries: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, Norway, Spain, Swe-

[1] The effects of concentration and competition in the banking sector are however generally ambiguous. According to some studies, concentration and competition could increase credit procyclicality. For example, Mandelman (2006) shows that markups are countercyclical and this monopolistic behavior increases the volatility of real variables.

[2] The PVAR model is performed on cyclical components since credit procyclicality refers to short-term fluctuations.

den, Switzerland, United Kingdom, and the United States.[3]

These 17 countries are split up into several clusters according to their banking system structure. Providing homogenous clusters is a complex task due to peculiar features in each banking system. We jointly consider several indicators to mitigate this issue and then to get consistent clusters. More precisely, we implement a hierarchical agglomerative clustering (HAC) combined with a partitional clustering (Lê et al., 2008; Husson et al., 2010, 2011) to account for similarities/dissimilarities in banking system structures evaluated on a set of variables. The PVAR models will be then estimated at the cluster level.

2.1 Clustering methodology

The HAC, based on an agglomerative algorithm, permits to built a hierarchy from individuals. In our case, individuals are countries characterized by their banking system structure. At the beginning, each country is considered as a separate cluster. The agglomerative algorithm progressively merges clusters according to their similarities, the latter being evaluated on multiple dimensions, i.e. on a set of variables. In each step, the pair of clusters with the lowest dissimilarities is merged into a single cluster.

We rely on seven variables to evaluate the degree of similarity in the banking system structures. More precisely, we account for concentration, ownership, restrictions in activities, and size of the banking sector. In addition, we distinguish between market-based and bank-based financial systems. The seven variables are the following:[4]

- $C3$: a concentration index given by the assets of three largest banks as a share of assets of all commercial banks,
- HHI: the Herfindahl-Hirschman index, defined as the sum of squared market shares,
- BC: total assets of commercial banks as a share of total assets of the banking system,
- $Rest$: a measure of a bank's restrictions to engage in securities markets, insurance and real estate activities,
- $Size^{GDP}$: private credit to GDP ratio,
- Cap: stock market capitalization to domestic assets of deposit money banks ratio,
- $Trad$: total value of stock transactions on domestic exchanges to private credit ratio.

Variables $C3$ and HHI are widely used to measure concentration in the banking sector. In addition, according to the traditional approach that associates more firms with more competition, these two indicators could also be considered as proxies for bank competition. The

[3] This sample of countries ensures data availability for the PVAR specification, and is also retained by Assenmacher-Wesche and Gerlach (2008, 2009) and Goodhart and Hofmann (2008).

[4] The seven variables do not play the same role in determining the composition of each cluster. Mean tests in Table 1 allow to assess this point (see Section 2.2). If mean tests show that a variable is not significant to characterize at least one cluster, removing this variable would have no consequences on clusters composition. For example, variable *Rest* is only significant to characterize cluster 1, at the 10% level. If this variable is removed, modifications of clusters composition concern only Australia which moves from cluster 3 to cluster 1.

ownership structure and restrictions in activities are also important to characterize banking systems. We use the variable BC, which measures the importance of commercial banks, to evaluate the ownership structures.[5] Indeed, commercial banks can behave differently from other types of banks (cooperative and savings banks). In particular, Ayadi et al. (2010) examine the performance and the role of cooperative banks in Europe. They underline that cooperative banks are not only profit-oriented and then pursue other objectives as mitigating intertemporal risk, which could smooth the credit cycle. Restrictions in activities are evaluated with the restriction index ($Rest$) proposed by Barth et al. (2001). This indicator measures the degree to which banks can engage in non traditional interest spread-based activities. The index ranges between 1 (least restrictive) and 4 (most restrictive). Barth et al. (2001) conclude that lower restrictions improve performance and stability of the banking sector. Finally, the size of the banking sector is examined through the credit to GDP ratio ($Size^{GDP}$). However, the degree of stock market development relative to banking system development should also be considered to evaluate if the financial system is rather market-based or bank-based. We rely on the ratio of stock market capitalization relative to bank assets (Cap), and the ratio of total value of stock market transactions relative to private credit ($Trad$) proposed by Demirguc-Kunt and Levine (1999). These indicators highlight if stock markets are large and active relatively to the banking system, i.e. if they compete with banks to finance the economy.

Concerning data sources, the variable $Rest$ is extracted from the World Bank's 2007 Regulation and Supervision database which contains data for the yearend 2005. Variables $C3$, $Size^{GDP}$, Cap and $Trad$ come from the World Bank's Financial Development and Structure database, and we compute averages over the 2004-2008 period. Variable BC is computed from the OECD database and also corresponds to an average over 2004-2008. Variable HHI is obtained from the ECB database and completed with data provided by Goddard et al. (2010) for non-European countries. This variable corresponds to an average over the 2004-2007 period.[6]

We need to specify the distance measure and the linkage rule to evaluate similarities in banking system structures based on our set of seven variables. The distance measure determines how the similarity of two countries is computed, and the linkage rule determines how the hierarchy is built. We rely on the Euclidean distance which is the most commonly chosen type of distance. We implement a principal component analysis (PCA) on standardized variables and the Euclidean distance is applied on a limited number of factors (not on raw data). This procedure allows both to manage scale differences between the seven variables used to char-

[5]Fractions of the banking system loans hold by government owned and foreign owned banks (available in the World Bank database) are also frequently used to characterize the ownership structure and have been considered in a preliminary analysis by the authors of the present paper. However, the fraction of the banking system loans hold by government owned banks is always very close to zero in our sample except for Germany. As a result, this indicator only leads to isolate Germany in the classification. Concerning the indicator on foreign owned banks, this variable was never relevant for clusters interpretability. Variable BC is therefore the most reliable to characterize the ownership structure.

[6]We use averages rather than yearly observations because the number of characteristics has to be inferior to the number of countries. Furthermore, variables $C3$, $Size^{GDP}$, Cap, $Trad$, BC and HHI do not record strong variations from 2004 to 2008, which implies that the use of averages rather than yearly observations is not crucial for the cluster composition. Note that this has been tested through the use of data from a single year, and the results obtained from the clustering methodology remain similar (the complete results are available upon request to the authors). In addition, the use of recent data allows us to deduce some policy recommendations from our results. Finally, working on averages instead of yearly data has the advantage to guard against the issue of non stationarity.

acterize banking systems and to denoise the data.[7] Husson et al. (2010) recommend to retain factors explaining a high percentage of variance, like 80% or 90%. In our case, considering only two factors would be insufficient since these two factors represent only 61.83% of the total variance, and then too much information would be suppressed. We then retain 3 factors which account for 79.01% of the total variance.[8] This choice may also be justified by the fact that, as highlighted by Husson et al. (2010), only factors that can be interpreted should be retained. At the 1% level, factor 1 is correlated with variables $Size^{GDP}$, $Rest$, Cap and $Trad$, factor 2 is correlated with variables HHI and $C3$, while factor 3 is correlated with variable BC. The first 3 factors allow therefore to account for the 7 variables, while the other factors do not have a particular meaning and are then considered as noise.

At the first step of the agglomerative algorithm, each country is considered as a singleton cluster and then similarities can be computed directly with the distance measure. However, from the second step, a linkage rule is also needed to determine the distance between clusters made up of several countries. We use the Ward's method that is generally viewed as very efficient. This procedure is based on an analysis of variance approach, it minimizes at each step the increase in variance for the pair of clusters being merged.

The hierarchy can be illustrated by a tree structure called a dendrogram. The latter represents how countries, initially considered as singleton clusters, are successively merged until to get all of the countries in the same cluster. The optimal number of clusters (i.e. where the tree structure should be cut) is generally based on the decrease of within-clusters inertia (variance) according to the number of clusters.[9] More precisely, we choose k clusters so that the number k minimizes:

$$\min_{k_{\min} \leq k \leq k_{\max}} \frac{W(k) - W(k{+}1)}{W(k\text{-}1) - W(k)},$$

where $W(k)$ is the within-clusters inertia obtained with k clusters. In addition, we consider $k_{\min} = 3$ and $k_{\max} = 10$ as suggested by Husson et al. (2010).[10] The rule retains k clusters so that the decrease of within-clusters inertia from k-1 to k clusters is high relatively to the one from k to k+1 clusters.[11] The optimal number k^* resulting from the minimization of this criterion indicates that a smaller number of clusters implies an important increase of within-clusters inertia, while a higher number of clusters does not lead to a substantial within-clusters inertia gain. According to the criterion minimization, we can conclude that the optimal number of clusters is 4.

[7]The first factors obtained from the PCA extract the most important information from the dataset. Denoising the data allow therefore to get more stable clusters than the ones obtained from raw data.

[8]For robustness check, we implemented the clustering methodology considering the 7 factors (which is equivalent to compute similarities on the 7 standardized variables since 100% of total variance is included). The clusters composition is not modified.

[9]The overall appearance of the dendrogram and clusters interpretability are also useful to determine the number of clusters.

[10]If $k_{\min} = 2$, the optimal number of clusters given by the criterion minimization is very often equal to 2 because the within-clusters inertia decreases sharply when moving from 1 to 2 clusters. However, in our case, considering $k_{\min} = 2$ would not modify the conclusion concerning the optimal number of clusters.

[11]The total inertia (which does not depend on k) is equal to the within-clusters inertia plus the between-clusters inertia according to the Huygens theorem. A decrease in within-clusters inertia correspond therefore to an increase in between-clusters inertia.

Figure 1 reports the dendrogram and illustrates how countries are successively merged to form four clusters. The HAC is useful to determine the number of clusters, but the agglomerative algorithm used in this method can never undo what was done previously. In other words, countries assigned to a cluster in the early stages cannot move to another cluster afterwards. Due to this constraint, the partition obtained from the HAC could be not optimal. Consequently, a partitional clustering, i.e. a k-means algorithm, can be used to improve (or consolidate) the partition obtained from the HAC. The k-means algorithm allows to move countries between the k clusters in order to minimize the within-clusters inertia.[12] The chosen partition, resulting from the k-means algorithm, is therefore not exactly similar as the one obtained from the dendrogram, but ensures that the k clusters are as distinct as possible. In our case, the k-means algorithm slightly modifies the partition obtained from the HAC. Only Canada moves from cluster 3 to cluster 1 so that clusters have the greatest possible distinctions. As a result, the clusters are composed as follows:

- cluster 1: Denmark, the Netherlands, UK, Ireland and Canada,
- cluster 2: France, Japan, Spain, Italy and Germany,
- cluster 3: Australia, Belgium, Finland, Norway, Sweden and Switzerland,
- cluster 4: the USA.

2.2 Clusters interpretability

Clusters interpretability is based on mean tests. More precisely, for each variable, we test if the mean for the cluster is equal to the overall mean. Following Lê et al. (2008), the test statistic is given by:

$$t = \frac{\bar{x}_q - \bar{x}}{\sqrt{\frac{s^2}{n_q}\left(\frac{N - n_q}{N - 1}\right)}} \sim T(N - 1)$$

where $\bar{x}_q$ and $\bar{x}$ are the averages of variable x respectively in cluster q and in the whole sample, n_q is the number of countries in cluster q, N is the total number of countries and s is the standard deviation of variable x for all the individuals. The t statistic follows a Student's distribution.

Table 1 in Appendix reports descriptive statistics together with the results of mean tests. The USA are assigned alone in cluster 4 which indicates that this country has a very specific banking system structure. Mean tests show that US specificities are mainly captured through the importance of stock markets relative to banking sector and through the weak concentration of commercial banks. The maximal values for the variables Cap and $Trad$, respectively at 2.1997 and 4.4213, are observed for the USA. In addition, the USA records the lowest concentration indicator $C3$ (31.77%). The USA has therefore the most market-based financial system and the lowest concentration of commercial banks. The specificity of the US banking system is illustrated on Figure 2. The latter corresponds to the map produced by the first two principal

[12] More precisely, the partition obtained from the HAC is used as the initial partition of the k-means algorithm. In a first step, the k cluster centers (centroids) are computed. In a second step, each country is assigned to the cluster that has the closest centroid. In a third step, when all countries have been assigned, the positions of the k centroids are recomputed. Steps 2 and 3 are repeated until the centroids no longer move.

components and highlights distances between countries.[13] The first principal component (i.e. the first dimension) accounts for 36.41% of the variance of the dataset and the second one for 25.43%. The USA clearly records the lowest value in the x-axis, corresponding to the first dimension, making it far from the other countries and assigned alone in a cluster.[14]

Countries in cluster 1, i.e. Denmark, the Netherlands, UK, Ireland and Canada, are characterized by a large credit market (in terms of GDP) mainly owned by commercial banks and with weak restrictions in activities. In particular, the credit to GDP ratio is 1.6032 in cluster 1 relative to 1.1854 in the whole sample, and commercial banks represent 95.17% of the banking sector relative to 83.33% in the whole sample. Concentration indicators and variables Cap and $Trad$ in cluster 1 are not significantly different from their corresponding averages in the whole sample. However, these indicators can indicate a few differences between countries merged in cluster 1. For example, variables Cap and $Trad$, measuring the importance of stock markets relative to banking sector, are much higher in UK (respectively 0.8281 and 1.3991) than in Ireland (respectively 0.3549 and 0.2789). Figure 2 illustrates the homogeneity within clusters, the centre (i.e. the barycentre) of each cluster being represented by a square. The distance between each country and the centre of its cluster allows therefore to sort countries within each cluster according to their degree of representability. In cluster 2, Denmark is the paragon (i.e the closest to the centre), while Canada has the lowest representability.

Countries in cluster 2, i.e. France, Japan, Spain, Italy and Germany, have a lower banking sector concentration. Indicator HHI in cluster 2 is 0.0415 while it reaches 0.1094 in the whole sample. In addition, countries in cluster 2 are characterized by a lower importance of commercial banks. Indeed, banking sectors in cluster 2 are made up of numerous cooperative and/or savings banks. Commercial banks represent 67.53% of the banking sector in cluster 2 against 83.33% in the whole sample. The variable $Trad$ indicates that countries in cluster 2 are rather bank-based than market-based although the p-value of the mean test is slightly up to 10%. Finally, concerning representability, Germany is the furthest from the cluster 2 centre, while France is the paragon.

Countries in cluster 3, i.e. Australia, Belgium, Finland, Norway, Sweden and Switzerland, are characterized by a strong concentration in the banking sector. Variables $C3$ and HHI in cluster 3 are respectively equal to 88.12% and 0.1766. In addition, stock market capitalization relative to total assets of banking sector (1.1682) is high although the p-value of the mean test is slightly up to 10%. The six countries in cluster 3 have however a few differences. For example, commercial banks are less important in Norway; the credit to GDP ratio is higher in Switzerland; Belgium is more bank-based than other countries. These differences are illustrated on Figure 2, Sweden being the paragon, while Finland and Switzerland are the furthest from the cluster 3 centre.

[13] The Euclidian distances between countries are not only computed on the first two principal components but on the first three principal components as previously mentioned. Considering the first two principal components is just convenient in a graphical perspective.

[14] Figure 2 highlights that the USA has specificities, but results obtained from the clustering methodology do not depend from that country. Indeed, in each step, the agglomerative algorithm merges the pair of countries (or group of countries from the second step of the algorithm) with the lowest dissimilarities. The USA would then be merged in one of the last steps of the algorithm, and then do not directly affect the cluster composition.

On the whole, the classification is meaningful in several aspects. Countries with larger banking sectors and lower restrictions in activities are merged in cluster 1. Banking sectors with a low concentration due to the presence of numerous cooperative and savings banks are merged in cluster 2. Smaller countries in which the banking sector is owned by a limited number of players are merged in cluster 3. The USA, with its strongly market-based financial system and a weak concentration of commercial banks, is assigned alone in cluster 4. Dissimilarities are minimized within clusters but it would be an illusion to expect countries perfectly homogenous within each cluster. As a result, some countries, for example Germany or Switzerland, have some specificities which make them to some extent less representative of their cluster. The partition obtained from the HAC and the partitional clustering is nevertheless optimal relatively to the set of indicators used to compare banking sectors.

3 The PVAR model

3.1 Data sources

We consider quarterly data over the 1986-2010 period for our sample of 17 OECD countries.[15] We retain the following variables: GDP, bank credit to the private non-financial sector, short-term interest rates and house prices. The GDP series are extracted from the OECD database and are directly available in real terms. All other series are also expressed in real terms using the consumer price index extracted from the OECD database. The bank credit to the private non-financial sector series are taken from the International Financial Statistics (IFS) database of the IMF, except for Canada (source: Statistics Canada), and Norway for 2007Q1 to 2009Q4 (source: Norges Bank). These credit series exhibit important level shifts notably due to changes in definitions. We have adjusted the series for these level shifts following the methodology proposed by Stock and Watson (2003): the growth rate of the observation affected by the level shift is replaced by the median of the growth rate of the two periods before and after the occurence of the level shift (see also Goodhart and Hofmann, 2008).[16],[17] The short-term interest rate is the money market rate taken from the OECD database, except for Japan (source: IFS), and Denmark and Finland for which some observations were missing for the year 1986 and have been complemented using IFS. Finally, house prices correspond to the Property Price Index obtained from the Bank for International Settlements (BIS).

Investigating credit procyclicality, i.e. short-term fluctuations, we focus on the cyclical components of time series rather than on levels or first differences. Credit cycle is then the main

[15]Note that, following Assenmacher-Wesche and Gerlach (2009), our sample starts in 1986 to avoid outliers observations due to the high-inflation period that ends in the mid 1980s.

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

[17]Considering the median rather than a moving average of order 4 allows to get smoother corrections since the median is not affected by the values of the largest and smallest growth rates. In addition, it seems more appropriate to correct the level shifts before starting the empirical analysis rather than introducing dummy variables in the PVAR model for two reasons. First, computation of credit cycle variables with the HP filter would be affected by the level shift. Second, considering dummy variables would reduce the number of degrees of freedom in the estimated PVAR model.

variable of interest in the PVAR specification. The business cycle is used to investigate the response function of the credit variable to a shock in GDP, interest rate and house prices being rather considered as control variables.

3.2 Cyclical components

In a first specification, we derive credit cycle and business cycle variables by isolating the cyclical components of credit and GDP series using the usual Hodrick-Prescott (HP) filter. More precisely, the HP filter is applied to the log transformation of seasonally adjusted series. The credit cycle is therefore represented by the percentage credit gap, and the business cycle by the percentage output gap.[18] Interest rate and house prices are also considered in their HP filtered versions to isolate the cyclical components. More precisely, our interest rate variable is the cyclical component deduced from the HP filter, while our house prices variable is the percentage gap obtained from the HP filter.

Several critics are frequently adressed to the HP filter (Kaiser and Maravall, 2000). In particular, the HP filter could lead to (i) imprecise end-point estimation, (ii) noisy cyclical signal, and (iii) spurious results. Harvey and Jaeger (1993) and Cogley and Nason (1995) particularly criticized the spurious cycles that the HP filter could induce. However, as argued by Pedersen (2001), if one defines business cycles in terms of an ideal high pass filter, then the HP filter cannot produce spurious cycles, because it well approximates an ideal high pass filter. To overcome the critics raised by Kaiser and Maravall (2000) and to improve the HP filter performance, we rely on two other specifications.

In a second specification, we consider the modified-HP (MHP) filter proposed by Kaiser and Maravall (1999) to extract cyclical components. The MHP filter relies on the TRAMO-SEATS procedures (Gomez and Maraval, 1996, 2000) in a first step.[19] The TRAMO procedure provides an automatic ARIMA modeling for time series. Time series can also be extended with backcasts and forecasts. The SEATS procedure then decomposes the ARIMA process into three unobserved components: trend-cycle, seasonal and irregular. Kaiser and Maravall (1999) suggest to perform the HP filter on the trend-cycle component obtained from the TRAMO-SEATS procedures. Compared to the usual HP filter, the MHP filter reduces the noise in the cyclical signal by removing the irregular component from the analysis. In addition, the extension of the trend-cycle component with backcasts and forecasts improve the estimation of start and end points. Moreover, using simulations, Kaiser and Maravall (1999) conclude that the spuriousness of cycles generated by the HP filter is “unwarranted”.

In a third specification, we use first differences of the trend-cycle component obtained from

[18] Considering a time series x_t, the HP filter determines the trend τ_t by solving:

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

where λ is the smoothing parameter. We set $\lambda = 1600$ as suggested by Hodrick and Prescott (1980, 1997) for quarterly data (see Pedersen (2001) and Ravn and Uhlig (2002) for discussions on the setting of λ). The cyclical component, i.e. the gap, is therefore given by $(x_t - \tau_t)$ and the percentage gap by $(x_t - \tau_t)/\tau_t$.

[19] TRAMO means Time series Regression with ARIMA noise, Missing observations, and Outliers and SEATS stands for Signal Extraction in ARIMA Time Series.

the TRAMO-SEATS procedures. Considering the first difference (FD) filter therefore allows to evaluate if results depend on the use of HP and MHP filters. Note however that the FD filter exacerbates high-frequency noise, downs weight the lower frequencies and introduces a phase shift into the data.

3.3 The PVAR methodology

In order to assess the link between credit procyclicality and banking sector structure, we consider the following PVAR model for each cluster:

$$Y_{i,t} = \alpha_i + A\,(L)\,Y_{i,t} + \varepsilon_{i,t} \tag{2}$$

where i denotes the country, $t = 1, ..., T$, $Y_{i,t}$ is the vector of endogenous variables, $\varepsilon_{i,t}$ is the vector of errors, α_i denotes the country-specific intercepts matrix, and $A(L)$ represents the matrix polynomial in the lag operator L—the number of lags being selected using the Schwarz information criterion. The vector $Y_{i,t}$ is given by:

$$Y_{i,t} = (FGDP_{i,t}, FCRED_{i,t}, Fi_{i,t}, FHOUSE_{i,t},)' \tag{3}$$

where $FGDP_{i,t}$ is the business cycle (i.e. the real GDP filtered series), $FCRED_{i,t}$ the credit cycle (i.e. the filtered series for the credit), $Fi_{i,t}$ the interest rate filtered series, and $FHOUSE_{i,t}$ the house prices filtered series. In addition, for each cluster, three PVAR specifications are estimated according to the filter used to construct the variables: HP, MHP and FD.

The interest of the PVAR approach is that it combines the traditional VAR framework—in which all the variables are endogenous—with the panel-data setup—in which unobserved individual heterogeneity is allowed. Turning to estimation issues, it is well known that the standard fixed-effect estimator is biased in dynamic panel specifications, due to the existence of correlation between the regressors and the fixed effects. The mean-differencing procedure commonly used to eliminate fixed effects would create biased coefficients. To overcome this issue, we consider the generalized method of moments (GMM) estimator. More precisely, we use forward mean-differencing, also referred to as the "Helmert procedure" (see Arellano and Bover, 1995; Love and Zicchino, 2006). In this procedure, to remove the fixed effects, all variables in the model are transformed into deviations from forward means, then each observation is weighted to standardize the variance. This transformation preserves the orthogonality between transformed variables and lagged regressors, so we can use lagged regressors as instruments and estimate the coefficients by the GMM procedure.[20]

Once the coefficients have been estimated, we compute the impulse-response functions (IRFs) by relying on the Cholesky decomposition to identify the shocks. We consider the following ordering:[21] $FGDP_{i,t}, FCRED_{i,t}, Fi_{i,t}, FHOUSE_{i,t}$, assuming that the GDP variable does not respond contemporaneously to any shock, while house prices respond contemporaneously

[20] Note that cluster 4 is made up of only one country. The GMM instrumentation is therefore not used to estimate the VAR model for this cluster.

[21] Recall that the usual convention is to adopt a particular ordering and allocate any correlation between the residuals of two elements to the variable that comes first in the ordering. The identifying assumption is that the variables that come earlier in the ordering affect the following variables contemporaneously, as well as with a lag, while the variables that come later affect the previous variables only with a lag.

to all shocks. The ordering of credit is based on the assumptions that movements in the stock of credit may immediately influence interest rates and house prices, and immediately respond to GDP, while credit is assumed to respond only gradually to interest rates and house prices movements.[22] Finally, we rely on Monte Carlo simulations to derive the IRFs' confidence intervals.

3.4 Results

To investigate the procyclical character of credit, we analyze at the cluster level the responses of the credit variable to a shock in GDP. To this end, Figure 3 displays the impulse-response functions, together with their 5% error bands. Three main comments can be drawn from these figures.

Firstly, considering methodological aspects, the IRFs are quite robust to the choice of the filtering method. More precisely, the HP and MHP filters lead to very similar results, while the responses seem to be more pronounced with the FD specification. Regarding the latter, it should however be mentioned that the confidence intervals are also larger. These differences may be explained by the fact that GDP shocks are higher when the FD filter is used, as shown in Figure 4. To account for this characteristic, we calculate scaled IRFs, by dividing the credit response function by the maximum of the IRF relating to the shock. Results displayed in Figure 5 report quite comparable patterns, showing the robustness of our conclusions to the choice of the filtering method: the GDP has a significant effect on credit, confirming the existence of credit procyclicality.

Secondly, compared to the three other clusters, cluster 4 displays a more pronounced response of credit to a shock in GDP. This apparent higher procyclicality should be considered cautiously due to the higher standard errors. Recall that this cluster is made of only one country, namely the USA. Consequently, the number of observations is lower than for the other clusters making the estimation more imprecise. The pattern of the US credit response function to a shock in GDP is thus more related to the small number of observations, rather than to the specificities of the banking system.

Thirdly, and on the whole, the results are very similar for the four clusters. This is especially true for clusters 2 and 3 with an immediate impact that remains significant during 10 quarters, the maximum being observed at period 6. In cluster 1, the response takes a few quarters longer to become positive, but it also lasts for about 10 periods and is approximately of the same magnitude than in the rest of the clusters. In cluster 4, the positive response becomes non significant before than in the rest of the clusters. Given that clusters 2 and 3 respectively refer to low and high banking sector concentration, our findings show that the banking system structure is not a key determinant of credit procyclicality. In addition, the fact that clusters 1 and 4 are not highly different in terms of credit responses to a shock in GDP shows that the nature—bank-based (cluster 1) or market-based (cluster 4)—of the financial system is not a key factor in explaining credit procyclicality. Finally, as expected, there is a positive and

[22]For robustness checks, we have also considered different other ordering to compute IRFs. The results were very similar to those presented afterward, and are thus not reported here to save space (they are available upon request to the authors).

significant response of GDP to shocks in GDP approximately of the same magnitude in all the clusters (see Figure 4).

Three main explanations for credit procyclicality may be found in the literature. The first one—known as the "financial accelerator"—is the presence of asymmetric information between borrowers and lenders (Bernanke and Gertler, 1995; Kiyotaki and Moore, 1997; Bernanke et al., 1999, among others). According to this proposition that relies on economic and financial cycles, informational asymmetries depend on the economic conditions. More specifically, in times of economic downturn associated with low collateral values, it may be difficult for borrowers—even with profitable projects—to obtain funding. Conversely, when collateral values rise with the upturn in economic activity, funding may be obtained by those borrowers through external finance, accentuating the economic recovery. A second explanation stressed by the literature deals with inappropriate market participants' responses to time-varying risk. As explained by Borio et al. (2001), those reactions mainly come from difficulties linked to the measure of the time dimension of risk, but may also be due to excessive responses of market participants to risk—even if the latter is correctly evaluated. The third explanation relies on the policy framework, given that the characteristics of prudential and accounting regimes obviously impact the financial system procyclicality through regulatory constraints.

We add to the literature by providing evidence that the banking sector structure, notably assessed by the degree of concentration or the importance of commercial banks, is not essential in explaining credit procyclicality. On the contrary, we show that banking sectors with various characteristics do not exhibit differences in terms of credit procyclicality. In this sense, asymmetric information, the inappropriate responses by financial market participants to changes in risk over time or other elements belonging to the policy framework remain stronger in order to explain credit procyclicality. In particular, in an attempt to reduce procyclicality in bank lending behavior, the focus should be placed on the micro and macro-prudential regulation rather than the structure of the banking system as a part of the regulatory framework.

4 Conclusion

The recent worldwide turmoil has highlighted significant weaknesses in the banking regulatory and supervisory system. Our aim in this paper is to investigate to what extent the banking sector structure is related to credit procyclicality. This is an important issue since an excessive credit procyclicality is usually seen as a source of financial instability. Bank regulators and other policymakers should consider the structure of the banking system as a part of the regulatory framework if credit is more procyclical in a specific banking sector.

Within this context, we aim at studying whether the credit procyclicality depends on the nature of the banking sector structure. This relationship between credit procyclicality and banking sector structure is investigated on a sample of 17 OECD countries over the 1986-2010 period. From a methodological viewpoint, we account for heterogeneity among economies and provide a meticulous classification of the banking system in our sample of countries. According to a hierarchical clustering methodology, the banking system is classified into the following four clusters: a) cluster 1 is characterized by a system with large banking sectors and lower restrictions in activities (Denmark, the Netherlands, UK, Ireland and Canada); b) cluster 2 is mainly bank-based with low concentration due to the presence of numerous cooperative and savings banks (France, Japan, Spain, Italy and Germany); c) cluster 3 can be regarded as having a strong concentration in the banking sector with a limited number of players (Australia, Belgium, Finland, Norway, Sweden and Switzerland) and d) cluster 4 is mainly a market-based financial system with the lowest concentration of commercial banks (USA).

We then estimate panel VAR models on the resulting sub-groups of countries. Our findings show that while credit significantly responds to shocks to GDP, the structure of the banking sector is not essential in assessing the procyclicality of credit for our group of OECD countries. Our findings rather suggest that in an attempt to reduce procyclicality in bank lending behavior, the focus should be placed on the micro and macro-prudential regulation.[23] Modifications in capital requirements, in bank provisioning practices or the introduction of a systemic risk regulation to dampen credit procyclicality do not need complementary measures on the banking system structure to supervise the degree of bank competition.

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[23]See for example the Geneva Report (2009), the Turner Review (2009), the Financial Stability Forum Report (2009), BIS (2009, 2010), Saurina (2009) or Repullo et al. (2009) about the different proposals to introduce countercyclicality into prudential regulation.

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Appendix

Table 1: Clusters interpretability

		$C3$	HHI	BC	$Rest$	$Size^{GDP}$	Cap	$Trad$
Whole sample	$Mean$	0.6875	0.1094	0.8333	2.1569	1.1854	0.8962	1.3769
	Std	0.2087	0.0788	0.1755	0.5416	0.3911	0.4830	0.9428
	Min	0.3177	0.0178	0.4296	1.0000	0.5810	0.3550	0.2789
	Max	0.9832	0.2628	1.0000	3.0000	1.7785	2.1998	4.4214
Cluster 1	$Mean$	0.6443	0.1132	0.9517^c	1.7333^c	1.6031^b	0.6292	0.8139
	t-$stat$	-0.5505	0.1264	1.7963	-2.0814	2.8418	-1.4274	-1.5420
	[p-$value$]	[0.5896]	[0.9010]	[0.0913]	[0.0538]	[0.0118]	[0.1727]	[0.1426]
Cluster 2	$Mean$	0.5722	0.0415^b	0.6753^b	2.2667	1.0853	0.5761	1.0831
	t-$stat$	-1.4702	-2.2947	-2.3957	0.5396	-0.6813	-1.7114	-0.8047
	[p-$value$]	[0.1609]	[0.0356]	[0.0292]	[0.5969]	[0.5054]	[0.1063]	[0.4328]
Cluster 3	$Mean$	0.8812^b	0.1766^b	0.8718	2.3333	1.0215	1.1682	1.5835
	t-$stat$	2.8261	2.5960	0.6679	0.9922	-1.2756	1.6639	0.6474
	[p-$value$]	[0.0122]	[0.0195]	[0.5137]	[0.3358]	[0.2203]	[0.1156]	[0.5265]
Cluster 4	$Mean$	0.3176^c	0.0273	0.7999	2.6666	0.5809	2.1997^b	4.4213^a
	t-$stat$	-1.8267	-1.0736	-0.1957	0.9703	-1.5929	2.6990	3.2293
	[p-$value$]	[0.0865]	[0.2989]	[0.8473]	[0.3463]	[0.1307]	[0.0158]	[0.0052]

Clusters composition: Cluster 1 is made up of Ireland, Denmark, the Netherlands, Canada and UK; Cluster 2 is made up of Spain, Germany, Italy, Japan and France; Cluster 3 is made up of Australia, Belgium, Finland, Norway, Sweden and Switzerland; Cluster 4 is made up of the USA.

Note: t-stat corresponds to the mean test statistic. a, b and c indicate significance respectively at the 1%, 5% and 10% levels.

Figure 1: **Dendrogram**

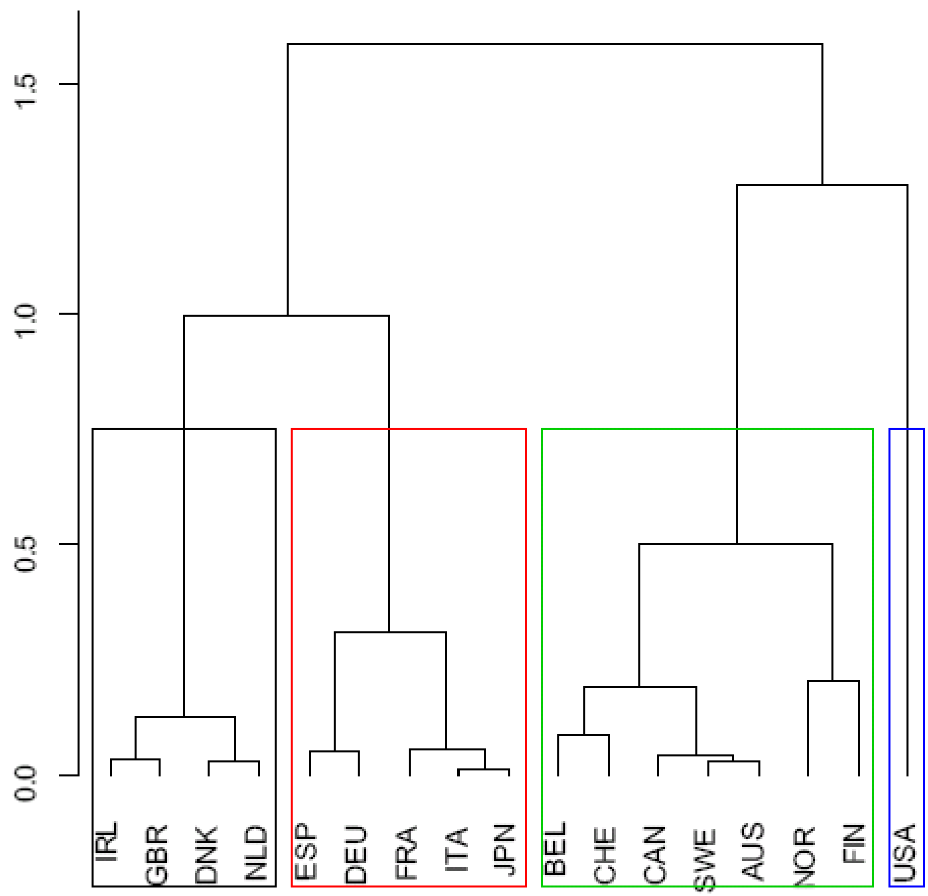


Figure 2: **Factor map**

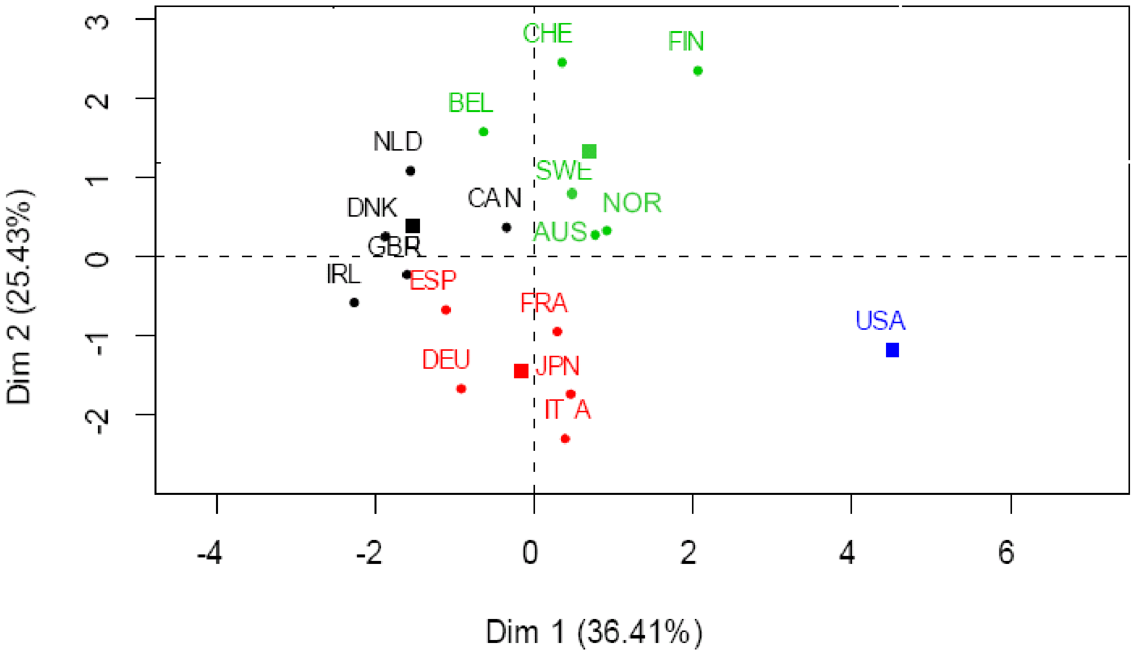
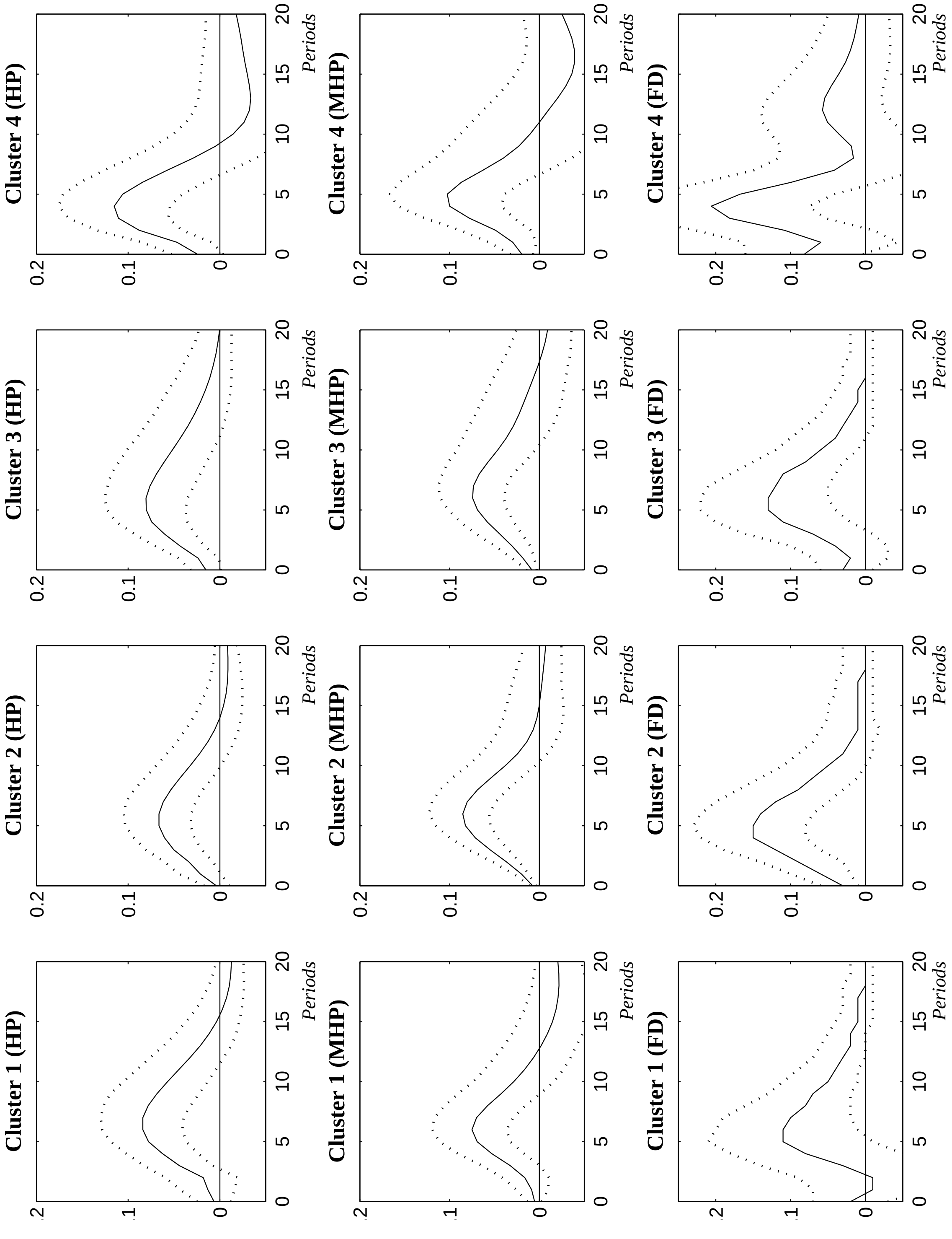
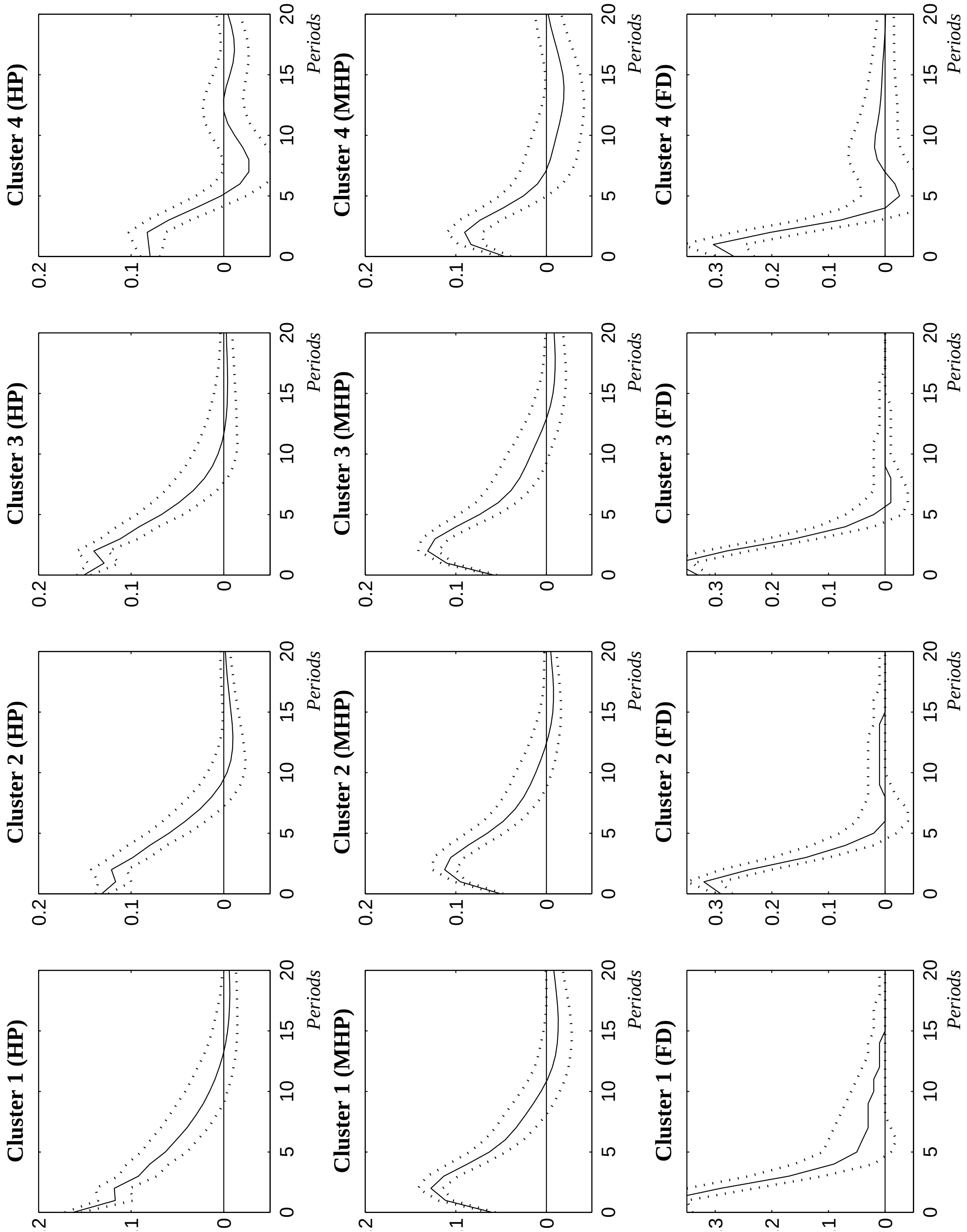


Figure 3: **Response functions of credit to a shock in GDP**[a]



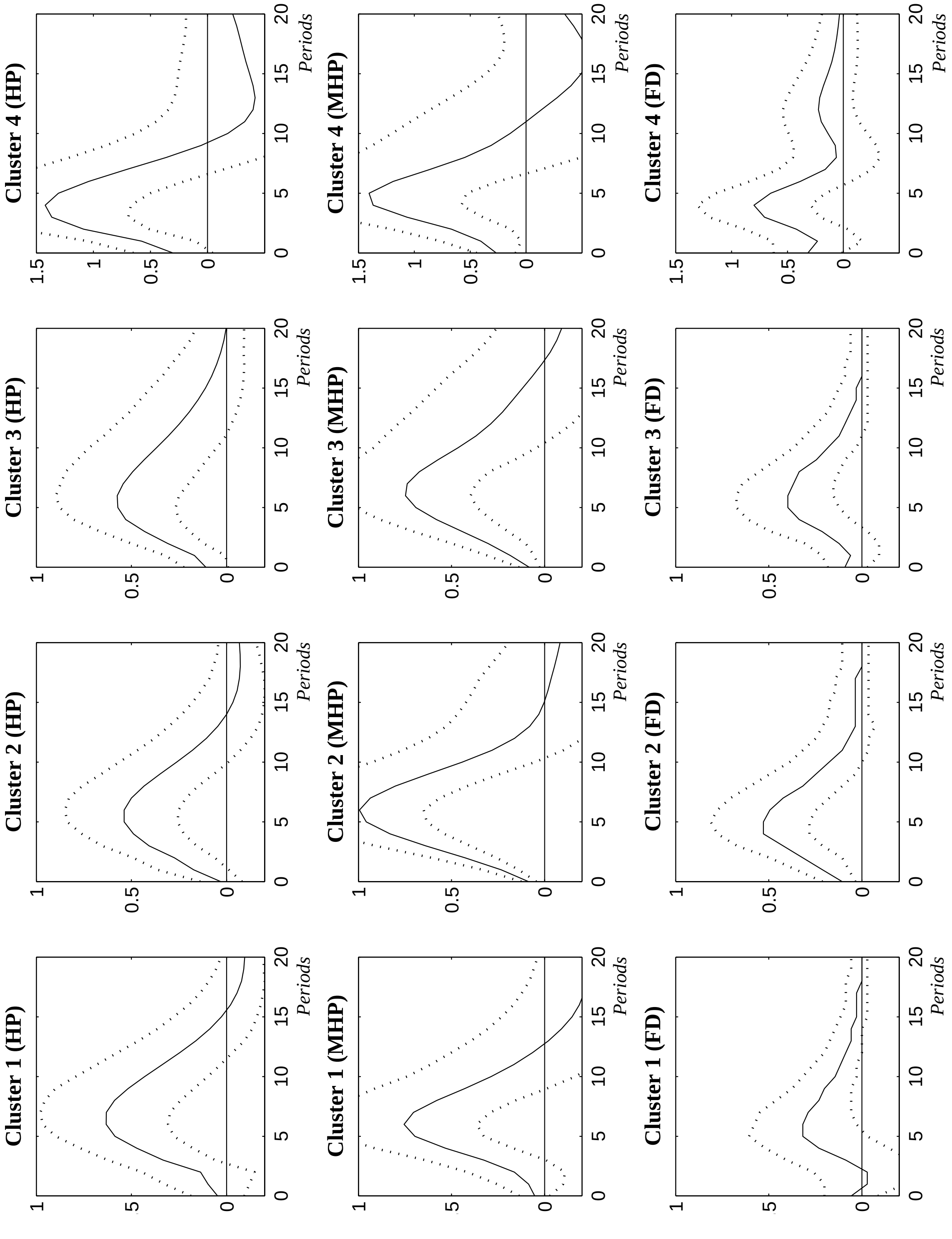
[a]**Note**: Cluster 1 is made up of Ireland, Denmark, the Netherlands, Canada and UK; Cluster 2 is made up of Spain, Germany, Italy, Japan and France; Cluster 3 is made up of Australia, Belgium, Finland, Norway, Sweden and Switzerland; Cluster 4 is made up of the USA. Estimations are made on filtered series; HP, MHP and FD indicate respectively that Hodrick-Prescott, Modified Hodrick-Prescott and First Difference filters are considered. Dotted lines represent the 5% error bands generated by Monte-Carlo simulations with 1000 reps.

Figure 4: **Response functions of GDP to a shock in GDP**[a]



[a]**Note**: Cluster 1 is made up of Ireland, Denmark, the Netherlands, Canada and UK; Cluster 2 is made up of Spain, Germany, Italy, Japan and France; Cluster 3 is made up of Australia, Belgium, Finland, Norway, Sweden and Switzerland; Cluster 4 is made up of the USA. Estimations are made on filtered series; HP, MHP and FD indicate respectively that Hodrick-Prescott, Modified Hodrick-Prescott and First Difference filters are considered. Dotted lines represent the 5% error bands generated by Monte-Carlo simulations with 1000 reps.

Figure 5: **Scaled response functions of credit to a shock in GDP**[a]



[a]**Note**: Cluster 1 is made up of Ireland, Denmark, the Netherlands, Canada and UK; Cluster 2 is made up of Spain, Germany, Italy, Japan and France; Cluster 3 is made up of Australia, Belgium, Finland, Norway, Sweden and Switzerland; Cluster 4 is made up of the USA. Estimations are made on filtered series; HP, MHP and FD indicate respectively that Hodrick-Prescott, Modified Hodrick-Prescott and First Difference filters are considered. Dotted lines represent the 5% error bands generated by Monte-Carlo simulations with 1000 reps.