Banks' financial conditions and the transmission of monetary policy: a FAVAR approach*

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Abstract

We propose a novel approach to assess whether banks' financial conditions, as reflected by bank-level information, matter for the transmission of monetary policy, while reconciling the micro and macro levels of analysis. We include factors summarizing large sets of individual bank balance sheet ratios in a standard factor-augmented vector autoregression model (FAVAR) of the French economy. We first find that factors extracted from banks' liquidity and leverage ratios predict macroeconomic fluctuations. This suggests a potential scope for macroprudential policies aimed at dampening the procyclical effects of adjustments in banks' balance sheets structure. However, we also find that fluctuations in bank ratio factors are largely irrelevant for the transmission of monetary shocks. Thus, there is little point monitoring the information contained in bank balance sheets, above the information already contained in credit aggregates, as far as monetary policy transmission is concerned.

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1 Introduction

The subprime crisis and the fears of a widespread credit crunch it has fueled over 2008-2009 in most developed economies has highlighted the importance of sound financial conditions of banks for the ability of monetary policy rate cuts to effectively curb the contraction in credit supply to the economy. Over the last decade, the dominant view of the monetary policy transmission mechanism mainly pointed to the importance of the expectations channel of monetary policy, where monetary policy influences output and prices merely through the expected path of future short term rates.[1] By contrast, the recent crisis helped dramatically to revive the complementary "credit" view, according to which banks' individual reactions to monetary policy decisions matter much for the overall level of activity. As in previous episodes of wide-ranging bank capital depletion, like in the US in the early 1990s or in Japan later in that decade (cf. Bernanke and Lown, 1991; Woo, 2003), empirical assessments of the bank lending and the bank capital channels have recently gained a heightened attention in both academic and policy circles (see e.g. Adrian and Shin, 2009a).

However, the practical relevance of the credit channel for monetary policy has been one of the most fiercely debated empirical issues in monetary policy for at least two decades.[2] Broadly speaking, empirical research has followed two main routes so far, one based on detailed individual bank information, the other based on measures of credit at the aggregate level, but both remain relatively inconclusive regarding the macroeconomic significance of financial frictions at the bank's level. We propose here a new approach that reconciles the use of both types of data: microeconomic bank data for a large population of French banks and a rich macroeconomic database for France. While the choice of this

[1] See for instance Blinder (1998), Bernanke (2004) and Woodford (2005).

[2] For a general perspective on the credit channel issue, and the usual distinction between the so-called *bank lending channel* and the balance sheet channel of monetary policy transmission, see Bernanke and Gertler (1995). For a view of this debate at the euro area level, see Angeloni et al. (2003).

country is partly dictated by issues of data availability, testing the importance of banks' financial conditions for monetary policy transmission is of particular interest in the case of France because its financial system is (still) largely bank-based rather than market-based.

As hinted above, a first strand of the applied literature has endeavoured to identify the role of bank heterogeneity and loan supply effects at the *micro* level, running panel data regressions on bank balance sheet data in order to investigate the determinants of individual credit fluctuations (see for instance Kashyap and Stein, 1995; Ehrmann et al., 2001). These studies have highlighted the impact of several banks' characteristics, such as total assets' size, capitalization and liquidity ratios, on a differentiated response of bank loans to monetary policy shocks. Typically, the traditional bank lending channel of monetary policy transmission appears then to be stronger for small, poorly capitalized and/or less liquid credit institutions.[3] However, a limit to the policy relevance of this literature is that little can be inferred from the results of micro data studies about the macro consequences of bank balance sheet constraints. As argued by Ashcraft (2006), on the basis of such panel data regressions, one cannot tell whether the financial frictions, at play in the bank lending channel and affecting for instance small banks, do really account for a significant part of the dampening of real activity that follows to a monetary policy tightening.

A second strand of the literature then relies on the estimation of small monetary VARs at the *macro* level, following notably Bernanke and Blinder (1992).[4] Indeed, impulse response functions derived from simple structural VAR models that factor in a few macro variables (e.g. GDP, inflation and a measure of the policy stance) provide a useful device for evaluating monetary policy transmission. By adding a credit aggregate variable to

[3]See for instance Kishan and Opiela (2000), Gambacorta and Mistrulli (2004), Engler et al. (2005) for the US, Italy and Austria respectively, and Loupias et al. (2002) for France.

[4]See also Ramey (1993), as well as Den Haan et al. (2007), Ehrmann and Worms (2004) and Hülsewig, Winker and Worms (2004) for more recent contributions.

this basic framework, it should be easy to gauge the impact of monetary policy shocks on total credit and the role of credit supply restrictions in economic downturns. In practice, however, things turn out to be trickier.

First, the estimated response of total bank loans to a monetary policy shock appears often to be muted and non-significant (Bernanke and Gertler, 1995). A closer inspection of the dynamics of various aggregate bank credit series -contrasting e.g. loans to households versus loans to non-financial firms, or short term vs long term loans- shows that this may result from a compensation effect of diverging responses of the main components in banks' loan portfolio (Den Haan et al., 2007; Mésonnier, 2008). In turn, this hints that a small VAR including only one credit variable is probably misspecified. A solution to this misspecification problem could then be to add several aggregate loan series to the VAR; but, as it is well-known, the inclusion of additional variables in standard VARs is restricted by the degrees-of-freedom problems.[5] Second, the information basis contained in a standard VAR with a handful of macroeconomic and aggregate credit variables appears to be too narrow, so that a proper identification of credit supply effects remains out of reach. As a matter of fact, by using a simple VAR framework, it is generally not possible to tell whether credit contracts after an interest rate hike because banks face a deteriorated balance sheet and then ration some borrowers within a process of deleveraging (loan supply effect) or because the deteriorated outlook has shifted down the demand for bank credit (loan demand effect). Overall, these limitations suggest that an empirical strategy that would rely on a data-rich environment *à la* Stock and Watson (2002) and would exploit information on heterogeneity in individual banks' financial conditions and the way they change through time could be more appropriate to detect the potential active role of banks in the transmission of the monetary policy shocks.

In this paper, we propose to examine the strength of the credit channel while reconciling

[5] Nevertheless, Giannone, Lenza and Reichlin (2009) propose to overcome this dimensionality problem and estimate such a large scale monetary VAR using Bayesian techniques.

the micro and macro levels of analysis into an integrated estimation framework. Following Bernanke, Boivin and Eliasz (BBE, 2005) and Boivin and Gianonni (2009), we employ a factor-augmented vector autoregression model (FAVAR) that we extend to explicitly include factors reflecting relevant fluctuations in a set of individual bank balance sheet ratios. A key feature of the BBE framework is to extract estimates of macroeconomic factors that affect the data of interest by exploiting the information contained in a large set of economic indicators. According to BBE (2005), the FAVAR framework leads to a better identification of the monetary policy shock compared to standard VARs, since it accounts explicitly for the large information set that central banks do monitor in practice and also because it does not require to take an 'ex ante' stand on the appropriate measure of economic concepts such as inflation or real activity, that are treated as latent common components. Finally, another appealing feature of the FAVAR approach is that the impulse response functions to a monetary policy shock can be computed for any variable included in the data set, while the dimensionality of the estimated VAR is kept reasonably low.

We implement this methodology in the case of France over the period 1993-2009, with quarterly data. The novelty of our approach consists in the parallel extraction of dynamic factors from large datasets of bank balance sheet indicators. Using French supervisory sources, we construct an original database of disaggregated bank financial ratios for a large set of French credit institutions, making up to 70% of total domestic bank credit. We consider this way, in our application, the information contained both in a macroeconomic database comprising a large number of macroeconomic indicators and in a microeconomic database. We then use the FAVAR setup to quantify the specific impact of banks' financial conditions, if any, on the response of key macroeconomic variables to monetary policy shocks.

While our methodology closely follows on Boivin and Gianonni (2009), who focus on the role of international factors in the transmission of US monetary policy, our interest in the role of bank level information is to our knowledge quite a novelty in the FAVAR literature. We are aware of only a few recent studies that go along a similar route. Gilchrist, Yankov and Zakrajsek (2009) extract unobserved factors from a broad array of corporate bond spreads and study the macroeconomic impact of shocks to these measures of credit risk in a FAVAR model of the US economy. Boivin, Gianonni and Stevanovic (2009) perform a similar exercise, but implement a different identification scheme of credit shocks which allows an economic interpretation of the (transformed) PCA factors. While close in spirit to ours, these studies do however not deal directly with monetary policy transmission and do not consider disaggregated bank data. By contrast, Dave et al. (2009) investigate the dynamic response of both credit aggregates and bank level loan growth measures to a monetary policy shock using disaggregated US bank data. However, they mainly focus on the differentiated responses of different types of loans, in the spirit of Den Haan et al. (2007), and do not use their FAVAR model to assess as we do whether fluctuations in banks' financial conditions (and their dispersion) significantly alter the transmission of monetary shocks to the broader macroeconomy.

Thematically, our work of course fits in with the abundant credit channel literature. However, more specifically, it can be related to a series of recent attempts to bridge the gap between microeconomic information about the health of financial institutions and the macroeconomy. Among these are recent studies by Adrian and Shin (2009b) that highlight the procyclical role of US investment banks' leverage, as well as somewhat earlier research by Peek, Rosengreen and Tootell (1999, 2003), who use a summary of US bank level supervisory information to identify the effect of loan supply shocks on GDP and its main sub-components.[6] The latter notably find that bank supervisory information predict macroeconomic fluctuations, and they provide evidence that this information is in fact used by the Federal Reserve to conduct monetary policy. However, they do not

[6]Their summary variable is the percentage share of bank assets that fall within the CAMEL 5 rating computed by the US Federal Reserve (i.e. the share of the riskiest part of the regulated US banking system).

formally examine the consequences of fluctuations in their bank health indicator for the transmission of monetary shocks.

Our main results are twofold. First, it appears that the first two principal components extracted from banks' liquidity or leverage ratios are quite correlated with industrial production and housing market conditions and that they predict macroeconomic fluctuations. This suggests a potential scope for macroprudential policies aiming at dampening the procyclical effects of changes in banks' balance sheets structure. Second, we nevertheless find that the fluctuations in banks' financial conditions do not matter much *per se* for the transmission of monetary policy shocks to the French economy. In other words, there is little point monitoring the information contained in bank balance sheets above the information already contained in credit aggregates, as far as monetary policy transmission is concerned.

The rest of the paper is organized as follows. Section 2 reviews the econometric framework and the estimation approach, with a detailed presentation of the data used in our estimation. In Section 3 we present the latent factors and the comovements between the macro and micro factors. Section 4 investigates the role of the bank-level factors in the monetary policy transmission mechanism. Section 5 concludes.

2 Econometric Framework: FAVAR

We aim to evaluate the importance of individual banks' financial conditions for monetary policy transmission in the case of France, a country for which we have access to a rich supervisory database. In other words, we seek to estimate to what extent the specific response of banks' financial conditions enhances or mitigates the effect of monetary policy on the economy. In this section, we first describe the empirical model and the estimation approach. This doing, we closely follow the lines of Boivin and Giannoni (2009).

2.1 Description of FAVAR

We consider an econometric framework based on a standard macro FAVAR model, that we extend to include additional factors summarizing the financial health of individual banks. We assume that the macroeconomic conditions can be adequately summarized by a $K \times 1$ vector of unobserved components or factors, C_t, while another $K^* \times 1$ vector of factors C_t^* is enough to describe the financial conditions of the banking sector. Note that, in what follows, the variables related to microeconomic information on banks will always be denoted with a star ($*$). In practice, we can assess the state of the economy and the health status of resident banks using (1) a large vector of macroeconomic indicators (denoted by X_t) and (2) a vector of individual bank balance sheet indicators for a large number of banks (denoted by X_t^*). These vectors are of dimension $N \times 1$ and $N^* \times 1$, respectively.

We assume that the macroeconomic indicators are related to the state of the economy and that disaggregated bank balance sheet ratios are related to the overall financial conditions of the banking sector according to the following observation equations:

$$X_t = \Lambda C_t + e_t \tag{1}$$

$$X_t^* = \Lambda^* C_t^* + e_t^* \tag{2}$$

where Λ and Λ^* are matrices of factor loadings and the $N \times 1$ (and $N^* \times 1$) vectors e_t and e_t^* stand for (mean-zero) series-specific components. By construction, these specific terms are uncorrelated with the common components C_t or C_t^* within each equation, but are allowed to be serially correlated and (weakly) correlated across indicators. Note that the number of common factors is assumed to be small relative to the number of indicators ($N > K$ and $N^* > K^*$). Within this framework, C_t and C_t^* represent two sets of components, common to all data series in each block and, in general, correlated across the two sides of the economy (macro conditions vs bank financial conditions).

The common factors should be understood as pervasive forces that drive the common dynamics of the data in each block, summarizing at each date either the state of the "real" economy or the financial strength of banks, as reflected by the equations (1) - (2). The variables in X_t are then taken as noisy measures of the underlying unobserved factors C_t. This means, for instance, that GDP growth, which belongs to the vector of macro series, is a noisy measure of "real activity", while the liquidity or leverage ratio of a bank j, which belongs to the vector of banking sector series, is a noisy measure of the financial health of the overall banking sector. We note that, in principle, it is not restrictive to assume that X_t depends only on the current values of the factors, since C_t might capture arbitrary lags of some fundamental factors.[7]

The dynamics of the common factors, i.e. the transition equation, are modeled as a structural VAR:

$$\Phi_0 \begin{bmatrix} C_t^* \\ C_t \end{bmatrix} = \Phi(L) \begin{bmatrix} C_{t-1}^* \\ C_{t-1} \end{bmatrix} + \begin{bmatrix} v_t^* \\ v_t \end{bmatrix} \tag{3}$$

where Φ_0 is a matrix of appropriate size on which we later impose some restrictions, $\Phi(L)$ is a lag polynomial of finite order, and the "structural" shocks v_t and v_t^* are assumed to be i.i.d. with zero mean and diagonal covariance matrix Q and Q^* respectively. These shocks are uncorrelated, but anyone of them may affect common factors of the other block (French economy versus banks' financial conditions) immediately or over time, through the off-diagonal elements of Φ_0 and $\Phi(L)$. By premultiplying both sides of (3) by Φ_0^{-1},

[7] Stock and Watson (1999) refer to (1) as a dynamic factor model.

the structural VAR has then the following reduced-form representation:

$$\begin{bmatrix} C_t^* \\ C_t \end{bmatrix} = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} C_{t-1}^* \\ C_{t-1} \end{bmatrix} + \begin{bmatrix} u_t^* \\ u_t \end{bmatrix} \tag{4}$$

where the reduced-form innovations u_t and u_t^* may be cross-correlated.

Since we are interested in characterizing the effects of monetary policy on the economy, we want to include in the vector of macroeconomic common components an observable measure of the monetary policy stance. As it is commonly the case in VAR studies of monetary policy in European countries, we consider here that the 3-months money market rate, R_t, (i.e. the 3-months PIBOR before 1999 and the 3-months EURIBOR afterwards) is an appropriate measure of the monetary policy stance in France over the period from 1993 to 2009. The short term interest rate is thus allowed to have a pervasive effect throughout the economy and is considered as a common component of all macro data series. This way, we can write

$$C_t = \begin{bmatrix} F_t \\ R_t \end{bmatrix} \tag{5}$$

where F_t is a vector of latent macroeconomic factors summarizing the behavior of the rest of the French economy.

2.2 Estimation

We estimate the empirical model using Boivin and Gianonni's (2009) variant of the two-step principal component approach developed notably by Stock and Watson (2002) and BBE (2005).

The first step consists of extracting separately principal components from X_t and X_t^* in order to obtain consistent estimates of the common factors under the structure laid out. As stated above, we impose the constraint that the short term interest rate is one of the factors for the set of macroeconomic series. This guarantees that the other estimated latent factors recover dimensions of the common dynamics that are not captured by the short term interest rate. Starting from an initial estimate of F_t, denoted by $F_t^{(0)}$ and obtained as the first $K-1$ principal components, we thus iterate through the following steps:

1. Regress X_t on $F_t^{(0)}$ and R_t, to obtain $\hat{\lambda}_R^{(0)}$.
2. Compute $\tilde{X}_t^{(0)} = X_t - \hat{\lambda}_R^{(0)} R_t$.
3. Estimate $F_t^{(1)}$ as the first $K-1$ principal components of $\tilde{X}_t^{(0)}$.
4. Back to 1.

As far as the common factors spanning individual bank balance sheet data are concerned, we do not impose any constraint in the first step. We simply estimate F_t^* as the first K^* principal components of X_t^*, where X_t^* collects series of individual bank ratios as explained below in the data section.

In the second step, the short term rate is added to the estimated macroeconomic factors F_t and the VAR in C_t and C_t^* (equation 4) is estimated. The matrix polynomial $\Psi_{21}(L)$ is then of particular interest, since it captures the lagged effect of banking conditions on macroeconomic factors. Note that the VAR coefficients $\Psi_{ij}(L)$ are identified provided that the variance-covariance matrix of the innovations $\left[u_t^{*\prime}, u_t^{\prime}\right]^{\prime}$ is non-singular. In particular, a sufficient condition for the coefficients in $\Psi_{21}(L)$ to be identified is that the factors standing for banking conditions do Granger-cause macroeconomic factors, an issue that we explore below.

2.3 Data Description

We use two distinct sets of data for the estimation of the FAVAR: a bank level one and a macroeconomic one, both over the period 1993:2 to 2009:1, with quarterly frequency. Regarding the first dataset, a distinctive feature of our study is that we make use of a large database of disaggregated bank balance sheet information as collected by the French supervisory agency (Commission bancaire). This database is particularly attractive because of its exhaustive coverage of all credit institutions chartered in France.[8] Nevertheless, its time depth is limited - bank balance sheets details are only available (with this broad coverage and under consistent reporting guidelines) since the first quarter of 1993. Although this tends to limit econometric investigations, it may also be noted that the year 1993 coincides with the adoption of Bank of France's independence by law, as well as with the launch of the last stage of the convergence process towards the EMU. This way, the period from 1993 to 2009 may be seen more convincingly as a single monetary policy regime, without any significant structural break (a point that we will discuss more in depth below, while presenting the impulse response functions computed from the FAVAR).

The macroeconomic dataset comprises 68 macroeconomic series, 60 series for the French economy and 8 series for the German economy. All macro series have been transformed to induce stationarity when necessary, as indicated in the Appendix. Other details about data sources and definitions are also provided in the Appendix. The inclusion of some key German series is motivated by the fact that the French monetary policy was largely tied to the monetary policy of the German Bundesbank during the run-up to the EMU and, notably, from 1993 on, within the frame of the European exchange rate mechanism. Including measures of both French and German activity, inflation and money prevents the implicitly estimated monetary policy function within the FAVAR to suffer

[8] Note that this balance sheet information is collected on a territorial basis, which means that credit granted by subsidiaries of French banking groups abroad is not reported.

from significant structural breaks due to the introduction of the euro and the consecutive delegation of the French monetary policy to the ECB. In particular, we rely on the fact that both countries, taken together, account for roughly half of the GDP of the entire euro area and behave (partly by construction) in a quite similar way to the euro area average which is the relevant aggregation level for the ECB since 1999.

Our initial bank-level dataset, with some 620 credit institutions at sample end, is not directly suitable for the purpose of factor analysis because of (1) the high degree of heterogeneity between institutions of different types and (2) the wide-ranging process of concentration within the French banking sector during the 1990s: indeed, the number of institutions shrunk by a factor 2.5 over the period from 1993 to 2009, implying that many banks were not observable over the whole period. Selecting an adequate sub-sample of banks involves thus a difficult trade-off. The right balance has to be struck between, on the first hand, keeping enough individual banks to catch something of the dispersion of banks' financial conditions in the estimated factors, and, on the second hand, discarding enough a-typical small institutions so that the few PC factors we extract from the final sample are economically meaningful.

To alleviate the heterogeneity issue and focus on "banks" as commonly understood (i.e. credit institutions whose business is to some large extent to collect deposits from the public and grant credits to non-financial agents), we first removed several categories of specialized credit institutions. These special categories include specialized financial institutions (such as leasing banks, customer credit institutions, factoring institutions etc.), municipal credit institutions and regional development institutions. We also dropped the regional branches of the three large mutualist and cooperative banks (in order to avoid double counting when the group head also reports for the entire network), the regional saving banks affiliated to a large savings bank network (whose individual ratios were suspected to be affected by important within-network transfers), as well as the branches of foreign held commercial banks (whose credit policy and financial health may be relatively immune to local economic conditions).[9] Finally, we also dropped commercial banks that operate only in the French overseas territories. Overall, this preliminary cleaning leaves us with a population of 105 banks at sample end, accounting for 77% of total customer credit and 79% of total assets in the initial database.[10]

At this stage of the database cleaning process, the population of banks remains still very heterogenous in terms of assets size and business profile. A quarter of these institutions are very small banks, mainly private banks, local banks or specialized institutions, with a total of assets below 500 millions euro each at sample end. Since the unobserved factors C_t^* are extracted by unweighted principal components analysis, keeping so many small banks implies that the information from the small banks ratios (that have little macroeconomic significance but are often more volatile) can have a disproportionate bearing on the estimated factors, which would be detrimental to their economic significativity. We thus chose to drop from the above selected categories the banks belonging to the first quartile in terms of mean total assets.[11] Besides, as the FAVAR approach requires a balanced dataset, we are forced to keep only the banks for which we have data over the entire period 1993-2009.[12]

Combined, these two steps reduced the population to a sample of 60 banks, making up nearly 71% of total customer credit (and 71% of total bank assets). For each of these

[9]For instance, Peek and Rosengreen (2000) show that the lending capacity of branches of Japanese banks in the US, in the late 1990s, was heavily constrained by the capital crunch faced by the mother institutions in Japan, leading to severe restrictions in the US commercial mortgage market.

[10]Customer credit is defined throughout as loans to non-banks in the supervisory database.

[11]The 26 banks thus discarded have average total assets below 405 millions euros over 1993-2009.

[12]This doing, we obviously created a potential for a selection bias problem. An alternative, often considered in papers running panel regressions on individual bank data, consists of reconstructing mergers and acquisitions backward in time, in order to keep information both from target and buying banks before the M&A (cf. for instance Loupias et al., 2002). This approach means in practice adding the corresponding balance sheet items of both banks prior to the merger. We think this method would be inappropriate for the purpose of our analysis, since it would end up creating individual measures of banks' financial health that did not exist in reality, adding this way uncontrolled sources of noise into the data.

banks, we constructed three different financial ratios as defined below in more details. Finally, a visual inspection of these ratios, cross-checked with the results of standard Bai and Perron tests of mean stability, revealed large statistical breaks for about half of these institutions, the bulk of them being again smaller banks accounting together for some 2% of total credit. We could check that these breaks are generally not explained by either acquisitions or changes of regulatory category, but may reflect other sources of statistical noise like changes in capital detention or business lines, about which we have no information in the database. We thus decided to correct for the biggest breaks using a simple statistical procedure along the lines of Den Haan et al. (2007). More precisely, for each ratio dataset, we computed growth rates of the ratio series and identified outliers as values distant from the cross sectional mean by more than 2.63 standard deviations. We replaced these outlier growth rates by the corresponding cross sectional means. Index ratio series were then reconstructed using the corrected growth rates and starting from the initial level values of the ratios. Finally, we dropped 8 banks, mainly market banks, that presented more than 20% outliers for at least one of the ratios.[13]

The resulting final sample consists of 52 commercial and cooperative banks accounting for 70% of total loans granted by all credit institutions at sample end (and 69% of total assets). Figure (1) shows the share of our sample in the total of bank loans over the whole period (1993:1-2009:1). This share increased somehow through time, staying between 66% and 70% since early 1997.

For each bank in the sample, we define three ratios that capture key dimensions of a bank's financial situation: one liquidity ratio and two leverage ratios, a total (or broad) leverage ratio and a credit (or narrow) leverage ratio. Both types of ratios have been identified in the empirical panel literature as important determinants of banks' reaction to monetary policy shocks, in line with the standard descriptions of the credit channel

[13] In the final ratio datasets, the outlier detection procedure implied a correction of 3% of the observations in the case of the broad leverage ratio, and less than 2% for the other ratios.

and the renewed versions of the same theory (like the bank capital channel of Van den Heuvel, 2002). The introduction of total leverage ratios is also motivated by Adrian and Shin's (2009c) recent findings that the total leverage of at least some US credit institutions is highly procyclical and their proposal that banks' leverage should be more closely and systematically monitored in a macroprudential perspective.[14]

We compute firstly an indicator of bank *liquidity* (labelled LIQ in the following), which we define as the ratio of liquid assets to total assets. Liquid assets are computed as the sum of cash, interbanking transactions, securities bought under repurchase agreements and securities held in the trading portfolio.

Secondly, we define our broad measure of *leverage* (LEV1) as the ratio of total assets to tier one capital. This broad leverage ratio is thus the inverse of the capitalization ratio often considered in earlier panel data studies.[15] Finally we also compute a narrow measure of leverage (LEV2), defined as the ratio of customer credit to tier one capital. Although less frequently used in the academic literature, this second leverage ratio is monitored by the French regulators on a regular basis, which motivates its inclusion in our study.[16]

Table (1) presents some descriptive statistics for our sample in 1999 Q1. Note that the sample, although relatively small and centered on banks of relatively close types, is still quite diverse along the standard dimensions explored by the credit channel literature, be it in terms of size (with total assets ranging from 268 millions euro to 1,390 bns euro), liquidity (with a ratio between 1% and 99%), or leverage (with a broad ratio between 1.2 and 125).

Factor estimation using principal components requires stationary times series.[17] Al-

[14] Regulatory capital ratios would have been equally interesting candidates, but this information was not available with enough time depth to be used in a time series analysis.

[15] See, for instance, Kishan and Opiela (2000) and Loupias et al. (2002) for the French case.

[16] Cf. for instance Commission bancaire (2009, p. 69 et sq.)

[17] Although simple methods have been proposed to estimate consistent factors from non-stationary panel

though it seems reasonable to assume from an economic point of view that bank ratios should be stationary, standard unit root tests reveal that it is not always the case from a statistical point of view in our sample.[18] Neglecting the results of such tests and keeping stochastic trends in the ratio datasets may lead to inconsistent estimates of the bank ratio factors and spurious correlations of these factors with the most persistent macroeconomic series in our database, in particular interest rates. We thus took the first difference of the individual ratio series that showed a unit-root at the 95% probability level, and left other ratios series unchanged.[19] Last, note that, following common practice, all macro and micro series were demeaned and standardized before extraction of the factors by PCA.

2.4 Specification of the FAVAR

The empirical model presented above is a dynamic factor model that links a large set of observable indicators to a small set of common components through the observation equations (1) - (2). The evolution of the common components is then specified by the transition equation (3) or its reduced-form representation (4). Theoretically, to the extent that we keep a sufficiently large number of common components from the PCA of each data block, the estimated factors collected in C_t and C_t^* span the same space than the unknown "true" factors or latent variables that drive the set of noisy indicators X_t and X_t^*. The issue of the number of factors selected is thus an important one in theory. In practice, however, there is still no clear consensus about the right analytical criteria for the choice of this number and numerous applications rely on judgemental or empirical evidence like, for instance, the change induced to the estimated impulse response functions (IRF) when new factors (accounting for a smaller part of the database variance) are added to the FAVAR

data (see the PANIC methodology by Bai and Ng, 2004), such methods are not suited for datasets mixing stationary and non-stationary series. Besides, the FAVAR approach requires stationary factors.

[18]We ran ADF tests with a constant and a number of lags selected according to the AIC.

[19]Between 64% and 83% of the ratios were considered as having a unit root, depending of the type of ratio.

model.[20]

In our case, it should be borne in mind that the class of specifications we can consider is severely constrained by the sample size (64 quarters of observations), which especially limits the number of lags in (4) as the number of factors gets larger. We want to include more than one common component from a given bank ratio dataset, in order to assess the potential impact of bank heterogeneity on the economy. Nevertheless, small sample size prevents us from including simultaneously common components from all three ratio datasets. We do then consider three distinct FAVAR models, replacing X_t^* with each of the three ratio datasets in turn.

We thus based the choice of the numbers of factors on two empirical criteria. Firstly, we computed Bai and Ng (2002) PCP2 and IC2 criteria, which indicated a maximum number of two factors for each of the three ratio datasets for the baseline sample of banks. Secondly, for each type of bank ratio, we estimated a FAVAR with up to six macroeconomic factors (including the short rate) and up to three common components from individual bank series. It appears that the form of the IRF to monetary policy shocks is quite robust to the inclusion of additional factors when at least four macro factors are included in the model. Whatever the bank ratio considered, our preferred specification of the corresponding FAVAR thus includes four macroeconomic factors and two bank ratio factors, and the transition equation (4) has 1 lag.[21]

[20]This is the route followed e.g. by BBE (2005), Boivin and Giannoni (2007) and Boivin, Mojon and Gianonni (2008).

[21]Results from standard tests of lag selection were mixed. The Schwartz information criterium suggested one lag in the various FAVAR models, generally in line with the Hannan-Quinn criterium, while the Akaike information criterium suggested from 2 to 5 lags depending on the model.

3 Bank balance sheets factors and macroeconomic dynamics

We first aim at clarifying how the factors summarizing French macroeconomic dynamics relate to disaggregated bank-level factors, as extracted separately from three microeconomic datasets of individual liquidity and leverage ratios. In this section, we thus use the common factors extracted from our various datasets and first determine the fraction of fluctuations in indicators of real activity, inflation, credit aggregates and interest rates that can be explained by macro and bank-level factors respectively. This first simple look at correlations and Granger causalities suggests that there is potentially a scope for a macroprudential regulation of banks' leverage and liquidity with a view of limiting the extent of macroeconomic fluctuations induced by banks' behavior. In the next section, we will then compare the impulse responses of various key macroeconomic variables when bank ratio factors are allowed to interact with macro factors or alternatively when this additional feedback mechanism is artificially shut down.

3.1 Interpreting the latent factors: a first look

We start by examining how the macro and bank ratio or micro factors are correlated with each others and with key macro variables, in an attempt to roughly characterize these latent factors. Figure (2) shows the estimated macro factors, while the bank ratio factors are plotted in Figures (3) to (5).

Table (2) first reports the correlations of the first three macro factors (excluding of course the short term interest rate, which we force to be the fourth macro factor as explained above) with a selection of macroeconomic variables. The first latent macro factor obviously stands for a measure of the business cycle, with a high positive correlation to GDP growth and its components and a negative correlation to unemployment. The second macro factor is also positively correlated with GDP growth, but can be more easily characterized as driven by longer term interest rates, while the third macro factors tends to capture the dynamics of inflation.

Table (3) reports the correlation of the micro factors, as extracted separately from each of the three bank ratio datasets, with the macro factors. The first LIQ component is strongly correlated with the business cycle macro factor (and with opposite sign with the short term interest rate), while the second bank liquidity component is mostly correlated with the second macro "long term rate" factor, and the correlation coefficients is smaller. The second LEV1 factor and the first LEV2 factor have similar correlation profiles and are strongly correlated to the short term interest rate. The other two leverage factors are also correlated with the "interest rate" and "business cycle" macro factors, but the correlation is weaker. Overall, these preliminary calculations confirm the intuition that banks adjust key dimensions of their balance sheets to fluctuations in real activity and market interest rate conditions. We do not know however to what extent such adjustments are active, as part of their asset-liability management policy, or passive, as an effect of changes in demand for credit. Neither can we determine on the basis of this evidence alone whether changes in bank conditions have an impact on macro conditions.

3.2 Comovements between macro and micro factors

In a second step, we investigate to what extent French macroeconomic variables are explained by macro versus bank-based factors. To do this, we regress each macro variable on the three macro factors (including the short term interest rate) or the first two bank-based factors obtained for a given type of bank ratio, taking each type of ratio in turn. Table (4) reports the fraction of variance of the series listed (i.e. the R^2 of the least squares regressions) that is explained by the macro factors and the bank ratio factors of each type (i.e. either related to liquidity or leverage, broadly or narrowly defined), respectively.

As apparent in the first row of the table, the entire macroeconomic dataset, X_t, is on average strongly correlated with the common factors. The R^2 of the macro factors is of

0.56, showing that the macro factors capture a good part of fluctuations in the French economy overall. As could be expected, the first three PCA factors of each set of individual bank ratios are less correlated with the macro series on average, with an R^2 of between 0.11 and 0.28, depending on the type of bank ratio considered.

When looking more closely at selected macroeconomic indicators, we first find that quarterly growth rates of real GDP, industrial production, HICP inflation, employment and non-residential investment present high correlations with the macro factors (R^2 statistics of 0.84, 0.88, 0.81, 0.80 and 0.67 respectively), while it is far less so for consumption (be it consumption of durable or non-durable goods). Macro factors also do a good job in tracking market and credit interest rates. The important point here is that most of the fluctuations in very cyclical variables are captured by only four macro factors. Note that the macro factors do also explain some 62% of the variance in house prices and 70% of the variance in housing loans.

Regarding the results of regressions on bank-level common components, we first find that bank liquidity and credit leverage factors explain a substantial part of the variance of housing prices (between 22% and 32%). The correlation with contemporaneous house price growth, while saying nothing about the direction of causality, highlights the fact that the recent boom and bust in housing prices over the last decade was largely associated with changes in individual banks' balance sheet. Rolling regressions over eight years period (not reproduced here to save space) show that this correlation was in fact higher, above 60%, over the decade from 1995 to 2005 which corresponds to the boom episode in France. Second, bank liquidity ratios are highly correlated with average bank interest rates for new loans, notably housing loans and investment loans to non-financial firms.

3.3 Do banks' financial conditions predict macro fluctuations?

The correlations discussed so far shed some light on the interrelation between macroeconomic conditions and the balance sheets of individual credit institutions. However, we do not know so far whether changes in banks' balance sheets are passively driven by the macroeconomy or whether they actively contribute to shaping the business cycle, as the bank lending channel would suggest, or at least can help to predict it.

In a first attempt at identifying the information content of banks' financial conditions for future macroeconomic conditions, we computed standard Granger causality tests within each of the three FAVAR models with bank ratio factors. Table (5) reports in rows the results of tests of the joint significance of bank-level factors of a given type (as stated in columns heads) in a regression of each macro factor over all lags of all macro factors and lags of the bank ratio components. Under the null hypothesis, bank-level factors have no predictive power. The upper panel reports results of estimations over the whole sample, while the lower panel restricts to the period before the onset of the subprime crisis in 2007Q3.

The results show that the three types of bank ratios do not have the same informational content for macroeconomic conditions. The information extracted from narrow (respectively large) bank leverage predicts three (two) of the macro factors over the whole period, and of up to four macro factors over the pre-crisis period (at the 10% level). In particular, bank leverage factors consistently predict the short term interest rate and the "business cycle" factor one quarter ahead. In contrast, factors summarizing bank liquidity mainly predict the second macro factor, and, over the pre-crisis period, the "business cycle" factor. By the way, these results confirm that the coefficients $\Psi_{21}(L)$ in the reduced form model (equation 4) are determinate, at least some of them.

While preliminary, the outcome of these causality tests suggests that microprudential regulations of liquidity or leverage of credit institutions should also matter in a macroprudential perspective.[22]

4 Implications for the Monetary Transmission Mechanism

We have documented so far that common components from key individual banks' balance sheet ratios commove with selected macroeconomic variables and, to some extent, drive changes in broad macroeconomic conditions. A natural question that arises then is whether the endogenous reaction of individual banks to an unexpected monetary policy impulse significantly alters the response of aggregate variables of interest (like GDP or consumer price inflation). The standard theory about the credit channel of monetary policy transmission suggests that the endogenous response of banks may amplify the effects of a monetary tightening, e.g. due to an increase in the external finance premium required by banks in face of an induced deterioration of borrowers' creditworthiness (financial accelerator effects) or, similarly, a rise in the external finance premium faced by banks following an induced deterioration in their own assets value (bank capital channel). Alternatively, theories of credit rationing suggest that capital shortages or liquidity constraints on the side of banks may, on the contrary, dampen the response of bank credit to monetary policy attempts at loosening overall financial conditions.

We investigate here this issue within the FAVAR framework presented above in section 2, following a general approach initiated by Boivin and Gianonni (2007). More precisely, we compare the impulse response functions (IRF) of selected macroeconomic variables to a 100 bp monetary policy shock under alternative hypotheses regarding the coefficients $\Psi_{21}(L)$ in equation 4, which links macro factors to lagged bank-level factors. The difference between the IRF when this block of coefficients is set to zero and when it is left unrestricted provides a measure of how important the endogenous response of individual banks' balance sheets is for the monetary transmission mechanism in France. In other words, the larger

[22] Note however that our measure of leverage is the total asset ratio to book equity capital, which significantly differs from the ratio of capital to risk-weighted assets usually monitored by bank supervisors.

the difference, the more a model of monetary policy transmission which includes only money and credit aggregates is misspecified.

A preliminary important issue is however whether the launch of the euro and the changeover from the Bank of France to the ECB from January 1999 on implies a regime shift for monetary policy in France or not. If it were the case, then nonlinearities should arise (at least) in the short term interest rate equation of our FAVAR, and we would not be allowed to investigate credit channel issues on the basis of linear VARs estimated over a time period that includes the date of EMU inception.

We think however that the assumption of no regime shift is amply vindicated in the case of France since 1993, the year when the Bank of France gained formal independence by law for the conduct of monetary policy. We base our position on both institutional and statistical arguments. First, as hinted above in section 2.3, French monetary policy was closely anchored to the policy conducted by the German Bundesbank and, indirectly, to German economic conditions between 1993 and 1999, when only because of the commitment of the Bank of France to peg the French franc to the Deutsche Mark in order to meet nominal convergence requirements during the run-up phase to the EMU. To reflect this, we included some key macroeconomic German series in our macro database, as detailed above in the data section. Second, French macro aggregates tend to commove strongly with the (reconstructed) euro area average since the mid 1990s. Since France and Germany both account for about 50% of overall euro area GDP, one should be comfortable with the idea that our macro factors are both quite relevant as summary ingredients of the reaction function of the Bank of France before 1999 and highly correlated with the euro area measures of activity and inflation the ECB is likely to respond to since 1999. Third, Boivin, Gianonni and Mojon (2008) have shown that the launch of the euro did not significantly affect the transmission of monetary policy shock in France and Germany. Fourth and last, we carried out standard breakpoint tests for our FAVAR models, positing the first quarter of 1999 as a possible break date. Table (6) presents the results of multivariate Chow sample-split tests. As it is well known that such tests tend to over-reject the null of no break in samples of common sizes, we followed Candelon and Lütkepohl (2001) and computed bootstrapped p-values (with 5000 replications). The results show that the null of no break in the FAVAR coefficients due to the inception of the euro is confirmed in all cases, at the 26% level for the "purely macro" model without bank factors and at levels above 56% for the models with LIQ, LEV1 and LEV2 bank-level factors.

Finally, figures (6), (7) and (8) show the estimated impulse response functions of selected macroeconomic indicators to an unexpected tightening of monetary policy by 25 basis points. In each figure, the solid lines represent the responses computed for the FAVAR model based on the sole macro factors while the dashed lines stand for the responses when the macro model is augmented with two common components extracted from one of the individual bank ratio datasets (LIQ, LEV1 and LEV2 respectively). The impulse responses are plotted along with the 70% confidence intervals.[23]

Regarding first the responses computed for the FAVAR model limited to the macro factors, the results look in line with usual findings and economic intuition. Following an unexpected monetary policy tightening, activity declines over the first 6 quarters and resume slowly thereafter. Industrial production gets back to its original level within three years, while GDP reverts more slowly. Investment, either residential or not, and inventories react more than consumption, while within consumption, consumption of durables is more negatively affected by an interest rate hike than is the consumption of non-durable goods. The rate of unemployment reacts sluggishly and employment, which reaches a low after three years, reverts very slowly to the original level, which may be consistent with conventional wisdom for France over this period. Interestingly, consumption prices

[23]We use Kilian's (1998) bootstrap procedure to compute the confidence intervals. Note that we bootstrap both the estimation of the factors and of the coefficients, so that the confidence intervals also account for estimation uncertainty about the unobserved factors.

as measured by the HICP decrease slowly over the first three years without the initial upswing or "price puzzle" that is often obtained within small macro VAR models. The response of the GDP deflator exhibits some price puzzle, but it is also more muted and globally non-significant. Housing prices react vigorously and on impact to an interest rate hike and reach their low within two years. Long term government bond yield as well as the various bank loan interest rates react also positively on impact to the monetary policy tightening. Interest rate on C&I loans, which are mostly short term loans indexed on short term market rates, adjust almost completely, while the pass-through of the short rate to interest rates on housing loans, which are in France mostly long term fixed rate mortgage loans, is significantly positive but muted, in line with previous findings for this country.[24] Regarding the response of the various types of bank loans at the aggregate level, housing loans decrease over the first two years, while corporate loans, and notably shorter term C&I loans, react positively in the short run and recede thereafter.

The "puzzling" positive response of short term C&I loans to a monetary tightening has already been documented on US data (cf. Kashyap and Stein, 1995; Morgan, 1998; Den Haan et al., 2007). Several types of explanations for this temporary increase can be found in the literature. A first line of reasoning points to a demand effect by firms, which may have to finance an inventory buildup following a monetary tightening or have to bear temporarily a higher cost for their working capital (cf. Bernanke and Gertler, 1995). Other authors look for supply effects by banks themselves, which may want to optimize the return on their credit portfolio and/or adjust their (risk-weighted) assets structure to keep complying with capital regulation in spite of the adverse effects of the monetary tightening on their interest revenues and hence on their equity base (cf. Van den Heuvel, 2002; Den Haan et al., 2007). These banks would therefore shift their portfolio towards short term loans and out of longer term credit, which either typically yield fixed interest rates (like mortgage loans) or require a higher capital coverage (like long term loans to

[24] Cf. for instance Coffinet (2005).

non-financial firms, at least under Basel I bank capital regulations). However, even if banks aim at reducing loan supply, this may be delayed by prevailing loan commitments to the benefits of larger firms, which account for the bulk of commercial bank credit. Indeed, large firms frequently borrow from commercial banks under loan commitment contracts so as to secure the volume and conditions of the loans they have over a pre-agreed period. As Morgan (1998) shows in the US case, loans without commitments do contract after a tightening monetary policy shock, while small firms also complain about tighter credit conditions offered by banks. Meanwhile, loans under commitments do not falter, or they even increase.[25] In our case, the significant positive short term response of inventories points towards a dominant role of credit demand by firms in the positive response of C&I loans to a monetary shock. Besides, the similar responses of these loans in the macro FAVAR and in the model augmented for common components extracted from total leverage ratios (LEV1) hints that the potential bearing of loans supply effects due to bank capital constraints is limited here.

Overall, figures (6), (7) and (8) show that the responses in the models with bank level ratio factors are very close, and at least not significantly different at the 70% level of confidence, to the responses obtained in the simpler models that include only macroeconomic information. Our exercise suggests thus that the specific reaction of individual banks to a monetary policy shock and the feedback of the induced changes in bank balance sheets on macroeconomic variables do not significantly alter the transmission process of monetary policy to the macroeconomy. This does not mean that the banking system and the way it interacts with non-financial private agents is a pure veil, but merely that the information already included in monetary macro variables like aggregate flows of bank credit for housing or corporate investment purpose is sufficient to capture the macroeconomic consequences of the credit channel. To that extent, the differentiated reactions to monetary

[25]Note that the argument about loan commitments may also be relevant to explain the shape of the response of bank loans for investment purpose.

policy shocks that are associated with heterogeneities in individual bank's balance sheet structures appear to be largely irrelevant from a macroeconomic point of view.

How do our findings relate with earlier literature? Considering the vast amount of studies on the credit channel, we find it more useful to focus this discussion on the differences between this study and two contributions by Ramey (1993) and Peek et al. (1999, 2003), which have particularly close connections with two dimensions of our approach.

In a somewhat older paper, Ramey (1993) did a counterfactual exercise that is formally close to the one we conducted in this section. Using a small scale VAR model of the US economy with four variables (output, money, credit and the Fed funds rate), she sets alternatively to zero the coefficients of the policy variable in either the money or credit equation, which is equivalent, she claims, to shutting down either the money or credit channel of monetary transmission. She then compares the impulse responses of output to a policy shock she obtains with either restricted models to the impulse response from the unrestricted VAR and concludes that the credit channel in unimportant in explaining monetary transmission. In his discussion of her paper, Bernanke (1993) sharply criticizes Ramey's reading of her results, pointing notably that (1) they are consistent with both the money and the credit views, as both views imply a quick reduction in bank liabilities, and that (2) this device alone cannot solve the age-old identification issue of bank loan supply vs demand effects. Although we agree with Bernanke's point, we think that they do not apply to the results presented in this paper. First, we are not interested in assessing the relative strength of the money channel (or, to put it in more modern terms, of the interest rate channel) vis-à-vis the credit channel in the particular case of the French economy. Since our macroeconomic database includes a list of credit aggregates and bank loan interest rates as well as monetary aggregates, our (restricted) baseline FAVAR with only macro factors does not exclude the possibility of operative bank lending and balance sheet channels. Our point is merely to assess the macroeconomic relevance of findings of the empirical literature in the vein of Kashyap et al. (2000), showing that individual banks with different characteristics in terms of notably liquidity and capitalization react differently to monetary shocks, which creates a potential for credit restrictions by at least some banks. Neither do we claim that we can identify (the absence of) loan supply effects using our methodology. Indeed, we cannot tell *a priori* whether changes in banks' financial conditions as captured by the factors are exogenous or driven by some other shocks to loan demand: even innovations to the second factors, which take more account of changes in heterogeneity of the ratios across banks, can reflect the adjustment to idiosyncratic, e.g. industry specific shocks that affect the customers of some banks more than others and thus the demand for credit addressed to those banks. To conclude on this, we thus do not read our results as proving that loan supply effects are unimportant. Instead, we just conclude that, at least in normal times, this heterogeneity in banks' financial conditions does not matter much for explaining monetary transmission at the macro level.

More recently, Peek et al. (1999, 2003) also tried to reconcile micro bank information with macro outcomes as they used detailed confidential supervisory information to construct an aggregate indicator of banks' financial health (the share of assets held by banks viewed by bank regulators as likely to fail, i.e. those with a "CAMEL" rating of 5). Running univariate regressions, they first find that their bank health variable (but no other summaries of bank leverage and liquidity ratios) contains useful marginal information to forecast unemployment and inflation up to four quarters ahead, which suggests that the Federal Reserve should look carefully at such bank level information from supervisory sources to conduct monetary policy. On the basis of PROBIT models of the Fed's target rate decisions, they also find that the Fed does actually take into account this information. In their second paper, they then provide evidence that shocks to their CAMEL indicator do reflect shocks to bank credit supply, which implies that part of the forecasting power of the bank health indicator for output has a causal interpretation. Our results contrast with theirs on two points. Firstly, contrary to part of their first findings, our Granger causality tests reported above suggest that even simple bank leverage ratios do help to improve forecasts of macroeconomic activity. Secondly and more importantly, Peek et al. (2003) do not formally examine, as we do, the consequences of monetary policy shocks, although they point in their conclusion to the relevance of their study for quantitative assessments of the bank lending channel. Instead, they focus on the (difficult) task of identifying loan supply shocks *per se* and show that such effects matter for US macroeconomic fluctuations. However, the mere fact that loan supply shocks exist and are important is a necessary but not a sufficient condition to prove that banks' reactions to monetary policy shocks, as a consequence of financial frictions that constrain adjustments to their balance sheets, do amplify the effects of the policy moves. Indeed, as Peek et al. (2003) show that their findings are robust when the bank health indicator has been priorily orthogonalized with respect to the Fed funds rate (and other state variables), one may think that it is the exogenous part in innovations to banks' health which matters (i.e. true loan supply shocks), not necessarily the endogenous reaction to other shocks. To conclude, their results do not contradict ours as far as the credit channel is concerned, but instead suggest interesting avenues for further research on the effects of shocks to banks financial conditions using our FAVAR framework.

5 Conclusion

In this paper we aim to quantify whether changes in banks' financial conditions at the microeconomic level matter at the macroeconomic level, notably by altering the monetary policy transmission mechanism. Using a unique and comprehensive database of individual bank balance sheets, we set up a FAVAR framework that allows us to summarize both overall macroeconomic conditions in the French economy and the financial conditions of banks resident in France with a small number of factors.

Within this framework, we first provide evidence that the information contained in three types of individual bank financial ratios -capitalization, liquidity and leverage ratios- explains a substantial part of macroeconomic fluctuations in some aggregate variables, most notably those related to the housing market (housing prices, residential investment and housing loans). Moreover, we find that the first two principal components extracted from individual bank leverage and liquidity ratios have a significant predictive power for macroeconomic conditions, which suggests that there is potentially a scope for active macroprudential policies aimed at constraining changes in these ratios.

Finally, we compare the impulse response functions of alternative FAVAR models that either allow for or restrict the feedback effects of bank-level factors on macroeconomic ones. We find that the information contained in individual bank ratios, including changes in balance sheets heterogeneity among banks, does not matter much for the transmission of monetary policy shocks.

This work could be extended in at least three ways. First, instead of following the methodology of Boivin and Gianonni (2009), we could implement the recently developed dynamic hierarchical factor model of Ng et al. (2009), whose advantage consists in distinguishing series-specific variations from two types of common variations: those from factors that are common to units within a block, and those from factors that are common across blocks. This could allow us to simultaneously consider the inclusion of all three kinds of bank ratios within the same FAVAR model. Second, it could be interesting to look at the effects of real demand shocks and see whether bank factors are relevant for the transmission of such shocks to the economy (as per the financial accelerator hypothesis). Finally, taking stock of the results of causality tests presented here and as suggested above by our discussion of Peek et al. (2003), we could investigate within a FAVAR framework the macroeconomic consequences of shocks to trends or dispersion in banks' leverage or liquidity conditions, in the spirit of the tests developed by Gilchrist et al. (2008). This is but left for further research.

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Appendix: Data Sets

1 - Macroeconomic series

Format contains series number; data span (in quarters); transformation code and series description as appears in the database. The transformation codes are: 1 - no transformation; 2 - first difference; 4 - logarithm; 5 - first difference of logarithm. The series were taken from Monetary Statistics database of Bank de France, Bank of International Settlement (BIS), EUROSTAT database, IN/IP INSEE database and OI/OP OECD database.

	France		
1	1993:1-2009:1	1	EMU 3-month EURIBOR, total, end of period
2	1993:1-2009:1	5	Total loans of French credit institutions, SA
3	1993:1-2009:1	5	Total loans to NFIs, SA
4	1993:1-2009:1	5	Loans to NFIs for cash needs, SA
5	1993:1-2009:1	5	Loans to NFIs for investing needs, SA
6	1993:1-2009:1	5	Total loans to households, SA
7	1993:1-2009:1	5	Mortgage loans to households, SA
8	1993:1-2009:1	5	Monetary aggregate M3, outstanding amounts at the end of the period (stocks)
9	1993:1-2009:1	5	Gross domestic product at market price, chain linked volumes, reference year 2000, SA
10	1993:1-2009:1	1	Production of total industry, index, SA
11	1993:1-2009:1	5	Final consumption of households and NPISH's (private consumption), chain linked volumes, reference year 2000, SA
12	1993:1-2009:1	5	Private consumption of households, durable goods, chain linked volumes, reference year 2000, SA
13	1993:1-2009:1	5	Private consumption of households, non-durable goods, chain linked volumes, reference year 2000, SA
14	1993:1-2009:1	5	Exports of goods and services, chained volume estimates, SA
15	1993:1-2009:1	5	Imports of goods and services, chained volume estimates, SA
16	1993:1-2009:1	5	Gross fixed capital formation of financial institutions, goods and services, SA
17	1993:1-2009:1	5	Gross fixed capital formation of public services, goods and services, SA
18	1993:1-2009:1	5	Gross fixed capital formation of households, goods and services, SA
19	1993:1-2009:1	5	Gross fixed capital formation of households, building and civil engineering, SA
20	1993:1-2009:1	5	Gross fixed capital formation of households, real estate services, SA
21	1993:1-2009:1	5	Gross fixed capital formation of NFIs, goods and services, SA
22	1993:1-2009:1	5	Gross fixed capital formation of NFIs, building and civil engineering, SA
23	1993:1-2009:1	5	Gross fixed capital formation of all sectors, goods and services, SA
24	1993:1-2009:1	5	Employees, full time equivalent, SA
25	1993:1-2009:1	5	Unemployment rate, BIT definition, SA
26	1993:1-2009:1	1	Increase in stocks, end of period (%)
27	1993:1-2009:1	5	Construction costs, total, cost of materials, NSA, Index, 1953 Oct = 100
28	1993:1-2009:1	5	Cost of construction: multiple dwellings, end of period
29	1993:1-2009:1	5	CAC40, end of day
30	1993:1-2009:1	5	Oil price, brent crude -1 month forward, level
31	1993:1-2009:1	5	GDP Deflator, index publication base SA
32	1993:1-2009:1	5	Consumer price index, harmonised, SA
33	1993:1-2009:1	5	Consumer price index, end of period
34	1993:1-2009:1	5	CPI (households, base 1998) - Food and non-alcoholic drinks
35	1993:1-2009:1	5	CPI (households, base 1998) - Alcoholic drinks

36	1993:1-2009:1	5	CPI (households, base 1998) - Clothing and footwear
37	1993:1-2009:1	5	CPI (households, base 1998) - Housing, water, gas, electricity and other combustibles
38	1993:1-2009:1	5	CPI (households, base 1998) - Furniture, domestic equipment and house keeping
39	1993:1-2009:1	5	CPI (households, base 1998) - Health
40	1993:1-2009:1	5	CPI (households, base 1998) - Transportation
41	1993:1-2009:1	5	CPI (households, base 1998) - Communications
42	1993:1-2009:1	5	CPI (households, base 1998) - Leisure and culture
43	1993:1-2009:1	5	CPI (households, base 1998) - Hotels, cafes and restaurants
44	1993:1-2009:1	5	CPI (households, base 1998) - Other goods and services
45	1993:1-2009:1	5	PPI - Buldings
46	1993:1-2009:1	5	PPI - Extractive industry, energy, water, wastes management and depolutting
47	1993:1-2009:1	5	PPI - Manufacturing industry
48	1993:1-2009:1	1	Long-term interest rate on government bonds
49	1993:1-2009:1	1	Average rate on loans to NFIs $<$ 1 year, new contracts
50	1993:1-2009:1	1	Average rate on loans to NFIs $>$ 1 year, new contracts
51	1993:1-2009:1	1	Average rate on consumer loans to households, new contracts
52	1993:1-2009:1	1	Average rate on mortgage loans to households, new contracts
53	1993:1-2009:1	1	Consumer confidence indicator, SA
54	1993:1-2009:1	1	Food-processing industry - production capacity utilization, %, SA
55	1993:1-2009:1	1	Consumption goods industry - production capacity utilization, %, SA
56	1993:1-2009:1	1	Automobile industry -production capacity utilization, %, SA
57	1993:1-2009:1	1	Equipment industry - production capacity utilization, %, SA
58	1993:1-2009:1	1	Intermediary goods industry - production capacity utilization, %, SA
59	1993:1-2009:1	1	Business climate in industry
60	1993:1-2009:1	1	Business climate in trade services
	Germany		
61	1993:1-2009:1	5	Monetary aggregate M2, outstanding amounts at the end of the period (stocks)
62	1993:1-2009:1	5	Gross domestic product at market price, chain linked volumes, reference year 2000, SA
63	1993:1-2009:1	5	Employees, persons (Thousands, SA)
64	1993:1-2009:1	5	Unemployed persons (Thousands, SA)
65	1993:1-2009:1	5	Gross domestic product, implicit price deflator, SA
66	1993:1-2009:1	5	HICP, SA
67	1993:1-2009:1	1	Consumer confidence indicator, SA
68	1993:1-2009:1	1	Long-term interest rate on government bonds

* NFI - non-financial institutions; NPISH - non-profit institutions serving households; PPI - Producer Price Index; SA - seasonally adjusted.

2 - Disaggregated bank balance sheet series

Format contains series number; data span (in quarters); bank identification code (CIB) and the name of the credit institutions as appears in the database. The ratios were computed using balance sheet information from the BAFI database of the French Banking Commission, Banque de France).

Liquidity and Leverage ratios

No.	CIB	Period	Credit institution
1	7	1993:2-2009:1	CUMUL BQ POP HORS AGREMENT COLLECTIF SCM
2	10057	1993:2-2009:1	STE BORDELAISE DE CIT IND ET COMMERCIAL
3	10096	1993:2-2009:1	LYONNAISE DE BANQUE L,B,
4	10178	1993:2-2009:1	BANQUE CHAIX
5	10188	1993:2-2009:1	BANQUE CHALUS
6	10228	1993:2-2009:1	BANQUE LAYDERNIER

7	10268	1993:2-2009:1	BANQUE COURTOIS
8	10468	1993:2-2009:1	BANQUE RHONE-ALPES
9	10558	1993:2-2009:1	BANQUE TARNEAUD
10	10638	1993:2-2009:1	CREDIT COMMERCIAL DU SUD-OUEST
11	11188	1993:2-2009:1	RCI BANQUE
12	11449	1993:2-2009:1	BANQUE THEMIS
13	11808	1993:2-2009:1	BANQUE FEDERATIVE DU CREDIT MUTUEL
14	12280	1993:2-2009:1	SOCRAM BANQUE
15	12869	1993:2-2009:1	BANQUE ACCORD
16	12939	1993:2-2009:1	BANQUE DUPUY DE PARSEVAL
17	13259	1993:2-2009:1	BANQUE KOLB
18	13539	1993:2-2009:1	BANQUE SOLFEA
19	17290	1993:2-2009:1	DEXIA CREDIT LOCAL
20	17679	1993:2-2009:1	STE DE BANQUE ET D'EXPANSION-SBE (2EME)
21	18029	1993:2-2009:1	BNP PARIBAS PERSONAL FINANCE
22	18189	1993:2-2009:1	CIE GLE DE CIT AUX PARTICULIERS CREDIPAR
23	18359	1993:2-2009:1	OSEO FINANCEMENT
24	18370	1993:2-2009:1	BANQUE FINAMA
25	18609	1993:2-2009:1	CAISSE CENTRALE CIT IMMOB DE FRANCE-3CIF
26	18839	1993:2-2009:1	B F T BANQUE DE FINT ET DE TRESORERIE
27	18889	1993:2-2009:1	CORTAL CONSORS
28	19239	1993:2-2009:1	NATIXIS TRANSPORT FINANCE
29	19269	1993:2-2009:1	GENEBANQUE
30	19870	1993:2-2009:1	STE DES PAIEMENTS PASS - S2P
31	22040	1993:2-2009:1	CONFEDERATION NATIONALE DU CREDIT MUTUEL
32	30002	1993:2-2009:1	CREDIT LYONNAIS
33	30003	1993:2-2009:1	STE GENERALE
34	30004	1993:2-2009:1	BNP PARIBAS
35	30027	1993:2-2009:1	BANQUE SCALBERT DUPONT - CIN
36	30047	1993:2-2009:1	CREDIT INDUSTRIEL DE L OUEST
37	30056	1993:2-2009:1	HSBC FRANCE
38	30066	1993:2-2009:1	CREDIT INDUSTRIEL ET COMMERCIAL - CIC
39	30076	1993:2-2009:1	CREDIT DU NORD
40	30087	1993:2-2009:1	BANQUE CIC EST
41	30488	1993:2-2009:1	FORTIS BANQUE FRANCE
42	30568	1993:2-2009:1	BANQUE TRANSATLANTIQUE
43	30958	1993:2-2009:1	BNP PARIBAS LEASE GROUP
44	31489	1993:2-2009:1	CALYON
45	39996	1993:2-2009:1	GROUPE CREDIT AGRICOLE
46	40168	1993:2-2009:1	BANQUE DE BRETAGNE
47	41199	1993:2-2009:1	BANCO POPULAR FRANCE
48	42959	1993:2-2009:1	ELECTRO BANQUE
49	43799	1993:2-2009:1	BANQUE DE GESTION PRIVEE INDOSUEZ - BGPI
50	43899	1993:2-2009:1	UNION DE BANQUES ARABES ET FRSES U B A F
51	44449	1993:2-2009:1	LIXXCREDIT
52	50140	1993:2-2009:1	CMP-BANQUE

Figures and Tables

Table 1: Descriptive statistics (2009Q1).

	Mean	Median	SD	Min	Max
Assets (billions of euros)	99.5	5.4	255	0.3	1390
% of total bank assets	1.3	0.1	3.4	0.0	18.6
Loans (billions of euros)	27.1	1.9	62.9	0.0	334
% of total bank loans	1.4	0.1	3.1	0.0	16.6
Liquidity (LIQ)	0.22	0.29	0.23	0.01	0.99
Broad leverage (LEV1)	20.5	29.1	26.1	1.18	124.7
Narrow leverage (LEV2)	8.0	11.6	11.23	0.18	50.52

Table 2: Correlations between the macro factors and selected macro variables.

Variable	F1	F2	F3
Interest rate	-0.49	0.50	0.15
GDP	0.57	0.69	-0.07
IPI	0.79	-0.44	0.22
Employment	0.75	0.39	-0.23
Unemployment	-0.65	-0.42	-0.02
Consumption	0.33	0.18	-0.19
Consumption durable	0.11	0.13	-0.14
Consumption nondurable	0.06	0.12	-0.10
Non-Res. Investment	0.67	0.43	-0.18
Inventories	0.78	-0.00	0.04
Res. Inv. by Hh	0.46	0.43	-0.02
Housing prices	0.58	-0.02	0.25
HICP	0.16	0.17	0.87
GDP deflator	0.20	-0.28	0.54
Total loans	0.61	-0.20	0.33
Housing loans	0.60	-0.47	0.30
Inv. corporate loans	0.54	-0.51	0.07
C and I loans	0.59	0.01	0.02
France 10y yield	-0.48	0.71	-0.01
Int. rate C and I loans	-0.57	0.60	0.08
Int. rate invt. loans	-0.72	0.55	0.13
Int. rate housing loans	-0.63	0.67	-0.11

Table 3: Correlation between bank ratio factors and macro factors.

Variables	F1 LIQ	F2 LIQ	F1 LEV1	F2 LEV1	F1 LEV2	F2 LEV2
Fmacro1	-0.70***	0.07	-0.33***	-0.47***	-0.61***	0.29**
Fmacro2	0.61***	0.39***	0.40***	0.47***	0.47***	-0.35***
Fmacro3	-0.05	-0.21*	0.00	-0.01	0.01	0.01
Interest rate	0.76***	-0.31**	0.38***	0.64***	0.67***	-0.49***

Note. * Denotes significance at 10% level. ** Denotes significance at 5% level.*** Denotes significance at 1% level.

Table 4: R2 for regressions of selected French macro indicators on various sets of macro and bank ratio factors (sample 1993:2 - 2009:1).

	All macro factors	LIQ factors	LEV1 factors	LEV2 factors
	(1)	(2)	(3)	(4)
All France data Xt (average over all French data)	0.56	0.24	0.15	0.17
Selected FR indicators				
Interest rate	1.00	0.68	0.56	0.69
GDP	0.84	0.16	0.02	0.00
IPI	0.87	0.83	0.62	0.71
Employment	0.80	0.11	0.02	0.05
Unemployment	0.68	0.03	0.03	0.04
Consumption	0.19	0.05	0.01	0.03
Consumption durable	0.05	0.01	0.03	0.01
Consumption nondurable	0.04	0.02	0.01	0.00
Non-Res. Investment	0.67	0.06	0.02	0.05
Inventories	0.69	0.27	0.23	0.26
Res. Inv. by Hh	0.46	0.06	0.01	0.01
Housing prices	0.62	0.32	0.22	0.33
HICP	0.81	0.01	0.00	0.00
GDP deflator	0.41	0.14	0.11	0.08
Total loans	0.56	0.28	0.14	0.16
Housing loans	0.70	0.57	0.43	0.48
Inv. corporate loans	0.60	0.49	0.25	0.33
C and I loans	0.45	0.13	0.08	0.08
France 10y yield	0.80	0.70	0.60	0.64
Int. rate C and I loans	0.89	0.71	0.62	0.78
Int. rate invt. loans	0.95	0.82	0.69	0.83
Int. rate housing loans	0.91	0.85	0.75	0.79

Table 5: Granger-causality tests for bank factors affecting macro factors. Table reports p-values.

	LIQ	LEV1	LEV2
All sample (1993:2009)			
F1	0.92	0.00	0.00
F2	0.00	0.15	0.08
F3	0.50	0.89	0.86
Interest rate	0.73	0.00	0.00
Before 2007-2009 crisis			
F1	0.02	0.06	0.06
F2	0.00	0.01	0.00
F3	0.21	0.02	0.05
Interest rate	0.21	0.00	0.01

Table 6: Multivariate Chow tests of a structural break in 1999 Q1.

	p-value (%)
Macro factors only	0.26
Macro + LIQ factors	0.56
Macro + LEV1 factors	0.58
Macro + LEV2 factors	0.57

Note. Bootstraped p-values (5000 replications).

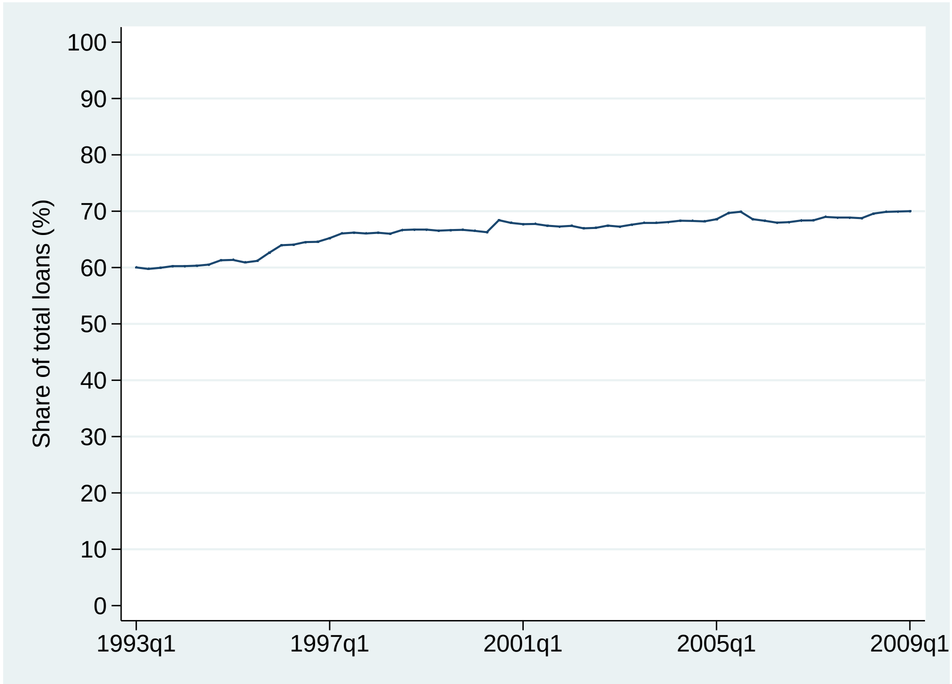

Figure 1: Share of the banks in sample in total loans granted by all resident credit institutions, 1993-2009.

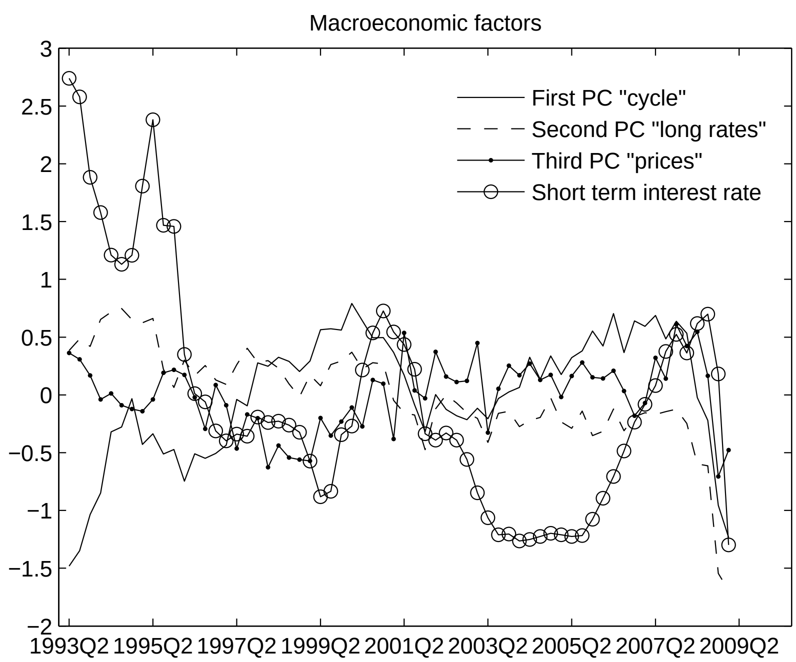

Figure 2: Macro factors.

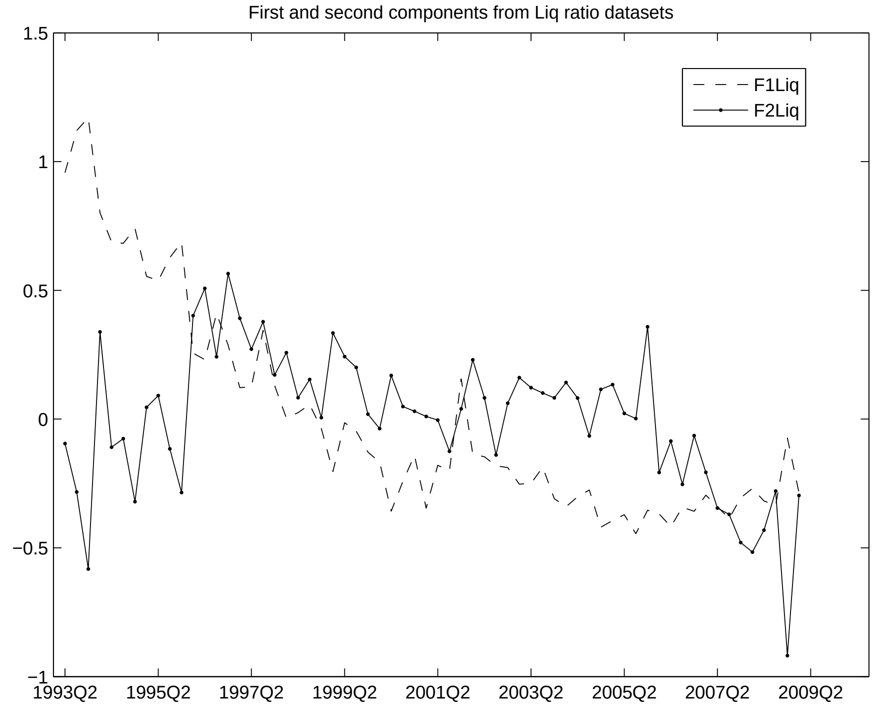

Figure 3: LIQ factors.

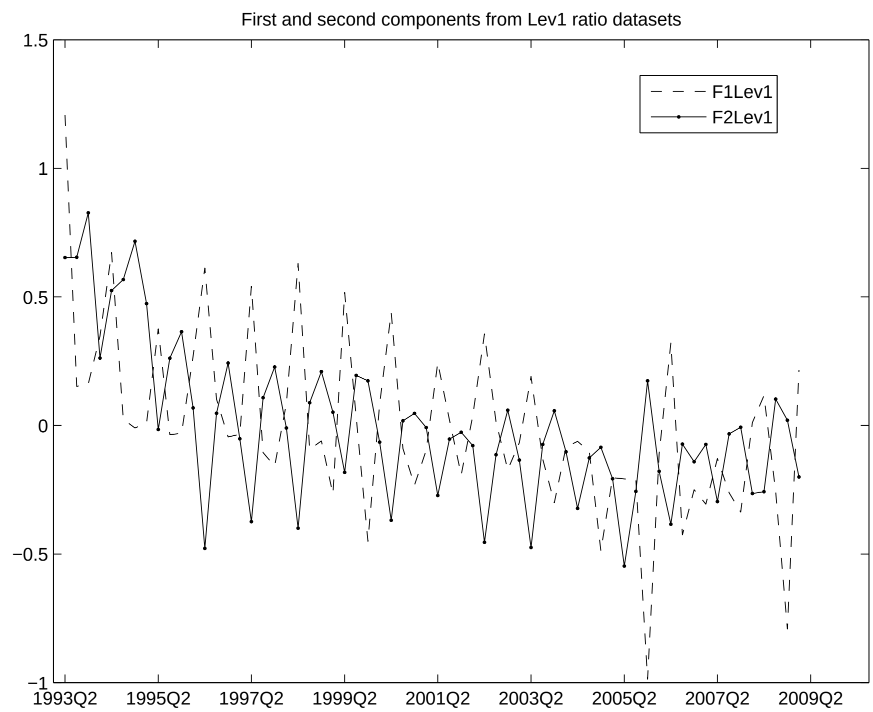

Figure 4: LEV1 factors.

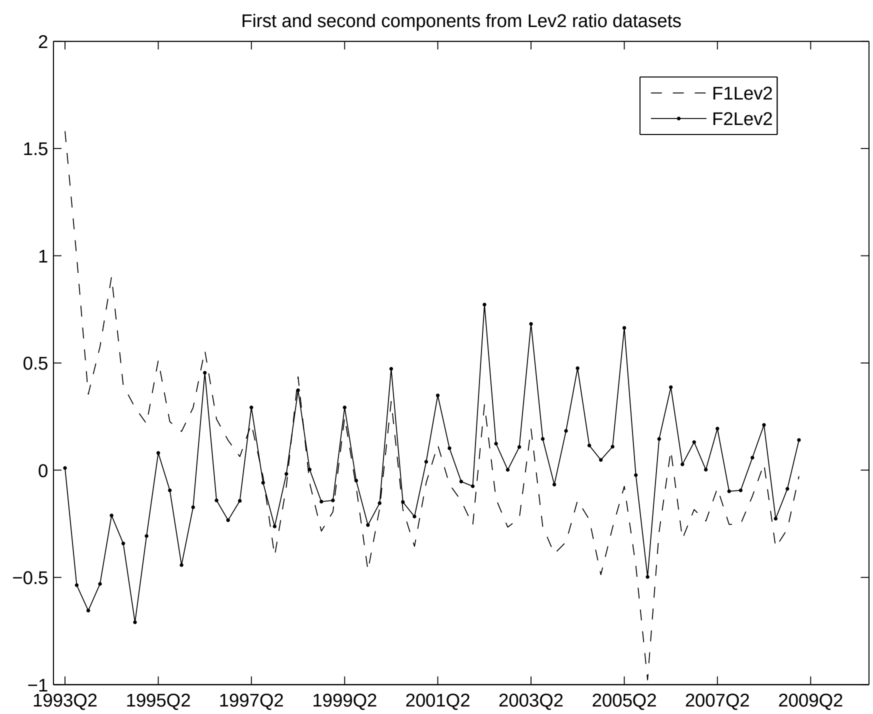

Figure 5: LEV2 factors.

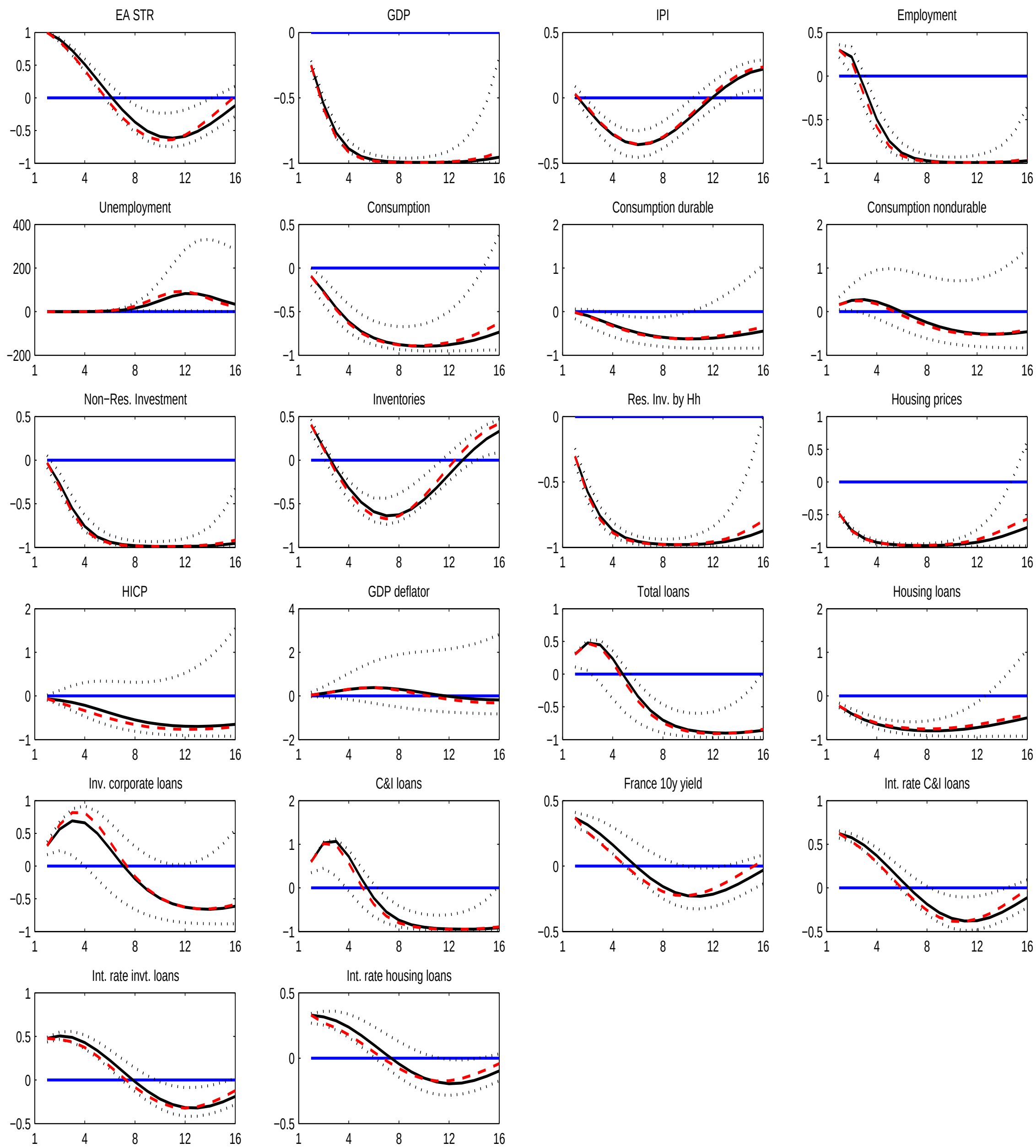

Figure 6: Impulse responses to an identified monetary policy shock. Model with macro factors only (solid line) vs model augmented with bank LIQ factors (dashed line).

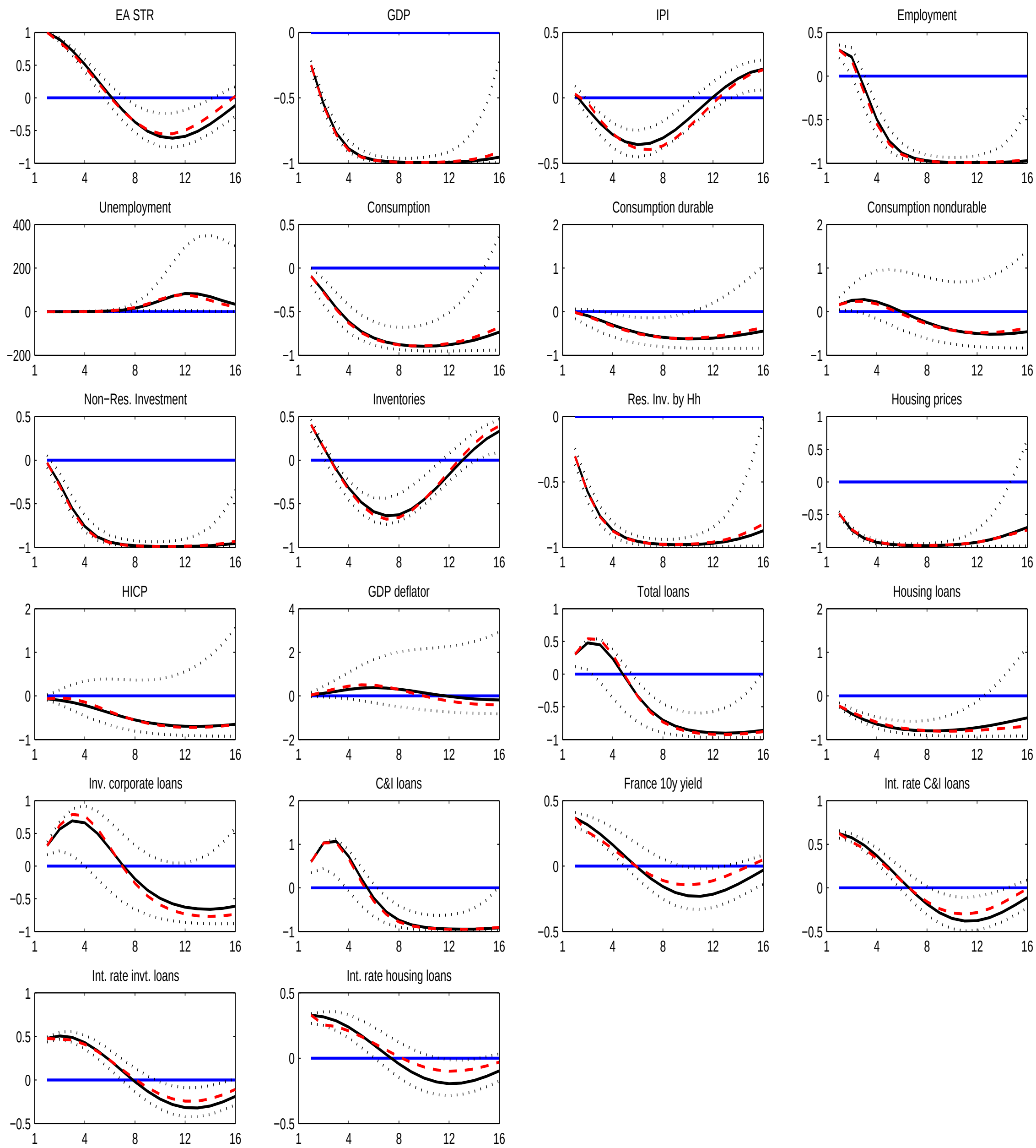

Figure 7: Impulse responses to an identified monetary policy shock. Model with macro factors only (solid line) vs model augmented with bank LEV1 factors (dashed line).

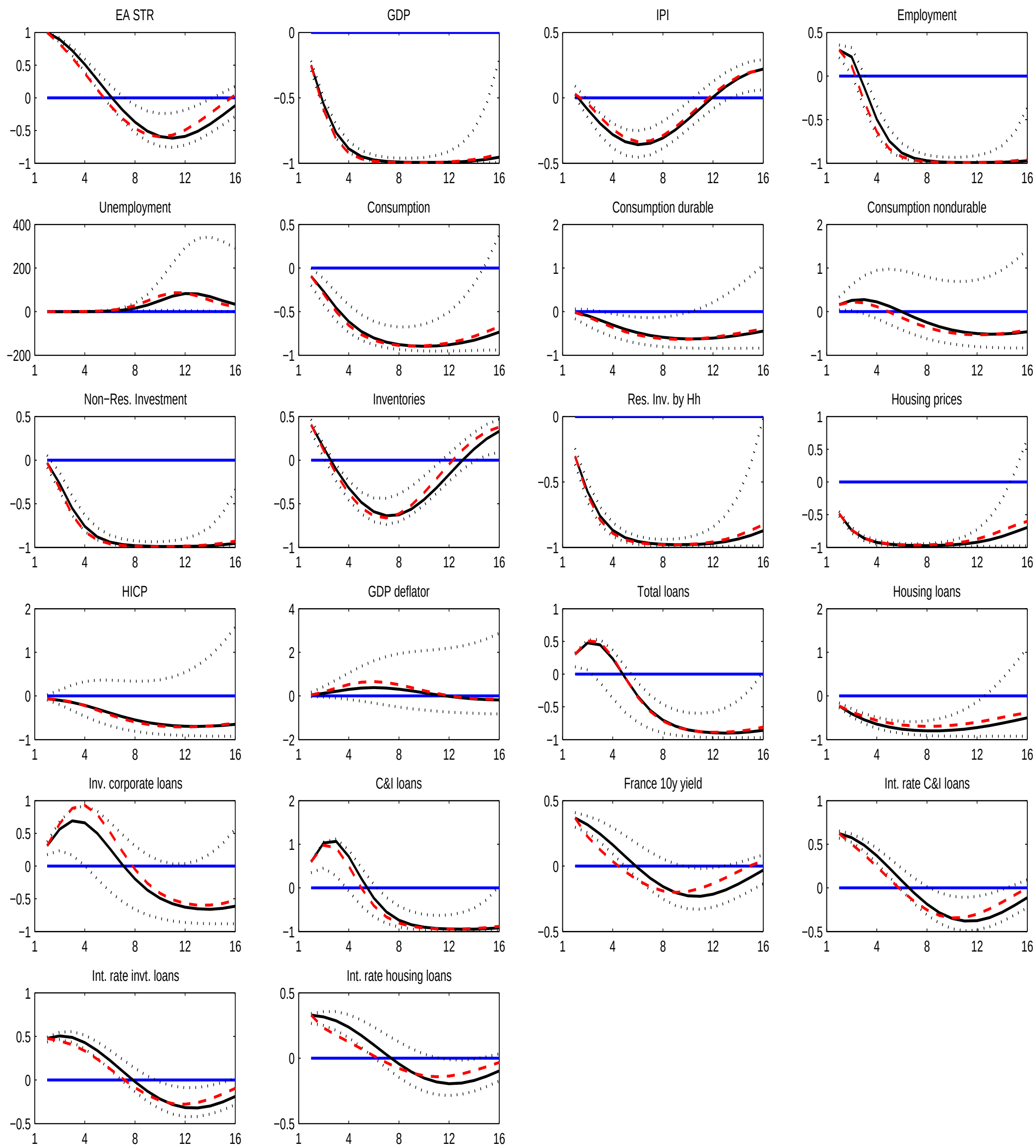

Figure 8: Impulse responses to an identified monetary policy shock. Model with macro factors only (solid line) vs model augmented with bank LEV2 factors (dashed line).