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Bank Leverage Shocks and the Macroeconomy : a New Look in a Data-Rich Environment

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Abstract:
The recent crisis has revealed the potentially dramatic consequences of allowing the build-up of an overstretched leverage of the financial system, and prompted proposals by bank supervisors to significantly tighten bank capital requirements as part of the new Basel 3 regulations. Although these proposals have been fiercely debated ever since, the empirical question of the macroeconomic consequences of shocks to banks' leverage, be they policy induced or not, remains still largely unsettled. In this paper, we aim to overcome some longstanding identification issues hampering such assessments and propose a new approach based on a data-rich environment at both the micro (bank) level and the macro level, using a combination of bank panel regressions and macroeconomic factor models. We first identify bank leverage shocks at the micro level and aggregate them to an economy-wide measure. We then compute impulse responses of a large array of macroeconomic indicators to our aggregate bank leverage shock, using the new methodology developed by Ng and Stevanovic (2012). We find significant and robust evidence of a contractionary impact of an unexpected shock reducing the leverage of large banks.

Keywords: Bank capital ratios, macroeconomic fluctuations, panel, dynamic factor models

JEL Classification: C23, C38, E32, E51, G21, G32

1 Introduction

Fluctuations in the leverage of large financial institutions have been identified as both a major driver of the accumulation of risks leading to the subprime crisis of 2007-2009 and an important amplification channel of the financial crisis itself, as well as a means of transmitting it to the real economy. For instance, Adrian and Shin (2010) have pointed out that, in a financial system in which the balance sheets of major institutions are continuously marked to market, leverage adjustments appear to be strongly pro-cyclical, thus fueling asset price booms as well as amplifying asset price busts. Based on the widespread view that on the eve of the financial crisis the leverage of many large financial institutions was overstretched and their core equity basis too narrow with respect to the risks really borne, bank supervisors worldwide swiftly reacted and proposed as early as the end of 2009 to significantly strengthen bank capital and liquidity regulations. The resulting so-called Basel 3 package of September 2010 thus notably includes a substantial increase in both the quantity and quality of core capital relative to risk-weighted assets, and also paves the way for the introduction of a new regulatory leverage ratio (i.e. unadjusted for estimated risks) towards the end of this decade[1].

Since then, the empirical question of the macroeconomic consequences of new regulations aimed at raising bank capital requirements has been the subject of a fierce debate and numerous investigations, both by academics and regulators. While the financial industry has produced alarming estimates of the potentially contractionary consequences of such regulations (IIF, 2010), claiming that more stringent capital regulations would imply higher bank funding costs and reduced lending, some researchers have argued that, at least in the long run, the Modigliani and Miller (1958) theorem should roughly apply and bank capital should not be that expensive (Admati et al., 2010). Searching for a robust empirical assessment, the Macroeconomic Assessment Group (MAG) associated with the Basel Committee has recently tried to assess the median impact on aggregate credit and real GDP of imposing higher capital requirements, based on the results of a large range of different structural and statistical models. Overall, the MAG's estimates point to only a modest recessionary impact of a transition towards higher capital standards, provided the phasing-in is progressive enough. Although the MAG produced an impressive amount of results in a very short period of time, their approach, based on an ad hoc combination of heterogenous and not necessarily consistent models, suffers from (acknowledged) method-

[1] Cf. Basel Committee on Banking Supervision (2010) for more details.

ological shortcomings in its attempt to reconcile the facts observed at the microeconomic (or bank) level with macroeconomic developments. Enough room is thus left for new empirical investigations.

In this paper, we propose a new approach to assessing the macroeconomic consequences of a shock to the capital-to-asset ratio of large US bank holding companies. A specificity of our work is that we base our estimates on an integrated framework that relies on a rich database of both bank balance sheet information and macroeconomic aggregates, thus bridging the usual gap in the literature between micro- and macroeconomic assessments of the effects of bank capital fluctuations on lending and growth.

Although a large literature has already tackled this issue, gauging the macroeconomic impact of a shock to bank leverage, as measured by a bank's capital-to-asset ratio, remains a difficult task.[2] A first identification problem arises from the fact that fluctuations in bank capital ratios, be they measured at the level of individual institutions or at the aggregate level, are partly endogenous to economic activity. Thus, they cannot as such inform about the extent of a contraction in credit supply as opposed to a decrease in credit demand or the consequences of a cyclical degradation in the credit quality of borrowers during recessions. Valid instruments are needed at the bank level but are not frequently available.[3] Alternatively, econometricians dealing with aggregate measures of financial leverage need to include sufficient controls for demand factors in their regressions and convince that they deal correctly with endogeneity issues, for instance by using VAR models. However, the identification of leverage shocks at the aggregate level in a VAR model often relies on ad hoc restrictions like the short-run restrictions imposed by recursive ordering and Cholesky decomposition (as in Berrospide and Edge, 2010). This merely reflects the fact that adequate information on bank behavior at the micro level is desperately missing.

A second well-known problem is that highlighting the role of bank capital constraints in bank lending at the individual level is not necessarily enough to understand their macro consequences.[4] Approaches exploiting the cross-sectional heterogeneity of bank capital at the micro level look more promising than macro VARs regarding identification issues, but remain generally unable to quantify the macro consequences of the effects that they identify at the micro level. Indeed, even if some banks tighten their supply of credit following adverse

[2] See e.g. Kashyap, Stein, Hanson (2010) for a recent survey.

[3] The classical studies by Peek and Rosengren (1997, 2000) of the consequences of a depletion of the capital of Japanese banks in Japan on their lending activity in the US provide a rare example of perfect instrumentation.

[4] Cf. for instance Ashcraft (2006) for a similar argument regarding assessments of the bank lending channel of monetary policy.

capital shocks, economy-wide effects hinge on the dependence of non-financial agents on credit from these banks to finance investment and consumption expenditures, as opposed to other sources of funding. Basically, a general equilibrium framework, when only in reduced form, is required to be able to reach any conclusion, with a proper multivariate modeling of a sufficiently large set of macro variables representing the economy and encompassing appropriate aggregate measures of bank capital developments.

Our approach aims to overcome these two identification hurdles. We proceed in four steps, making use of both bank-level and macroeconomic information in an integrated framework. First, we estimate the vector of "non bank-related" macroeconomic shocks that drive the bulk of US aggregate business cycle fluctuations. We extract these shocks, that we do not need to identify individually, from a large macroeconomic database using a standard dynamic factor model as in Stock and Watson (2005). This macroeconomic database includes a variety of real, nominal and financial indicators, but no aggregate variable that has any direct link with bank balance sheets (such as e.g. credit or money aggregates or aggregate measures of bank lending rates and conditions). Second, we construct measures of exogenous capital ratio shocks at the bank level, using a dynamic model of bank capital ratios that we estimate on an unbalanced panel of US large bank holding companies over the period from 1986 to 2010 with quarterly frequency. In doing this, we include as controls in our panel regression the space spanned by the macroeconomic shocks that we have obtained from the first step. As a consequence, we can be confident that the estimated innovations to individual bank capital ratios are orthogonal to whatever non credit-related shocks are needed to explain most of the fluctuations in the real variables of interest. Third, we aggregate these individual capital ratio shocks into a macroeconomically relevant measure of exogenous shocks to the leverage of large banks. Last, this time including credit and other banking indicators in the list of dependent variables, we estimate the impulse responses of a large set of macroeconomic variables to this new series of aggregate bank leverage shocks, using the Factor-augmented Autoregressive Distributed Lag (FADL) methodology recently proposed by Ng and Stevanovic (2012).

We find robust evidence that our measure of leverage shocks to the large US banks matters for understanding fluctuations in credit aggregates as well as the US business cycle. In particular, an unexpected rise in the capital to asset ratio of large banks (akin to a negative bank leverage shock) triggers a significant and persistent fall in the growth of loans across the board, as total commercial bank credit contracts by some 1% on impact for a shock of 10 basis points, and by about 3% after six quarters. This impact is larger on loans to non-financial firms than on real estate loans. Meanwhile, interest rates on commercial and industrial loans shoot up on impact, which suggests that our capital ratio shock series indeed correctly indentifies negative credit supply shocks. On the real activity side, investment, consumption of durable goods and GDP also fall significantly on impact, although this fall is more short-lived, suggesting that at least some non-financial agents may be able to compensate for the reduction in credit supply and turn to other sources of funding.[5] Of course, some caution is required in interpreting these results in terms of the likely impact of *regulatory* capital tightening. Indeed, the innovations on which we base our aggregate capital ratio shock series may reflect a variety of disturbances: stricter requirements imposed by the regulator or market discipline is one possibility, but another could be unexpected profits and losses due to some asset price fluctuations during the quarter going beyond expectations based on the information available to bank managers at the beginning of the quarter or not reflected in contemporaneous shocks affecting the real economy. Nevertheless, if we allow for an asymmetric effect of leverage-reducing and leverage-increasing shocks on macro aggregates, we find that the former matter much more that the latter. This hints that leverage-reducing shocks may impinge on bank credit because they make capital requirements more constraining. Finally, we compare our results with the macroeconomic responses we obtain when we plug the measure of aggregate leverage shocks estimated by Berrospide and Edge (2010) into our FADL setup. This comparison suggests that taking advantage of the information contained in the bank data has helped us better identify the variations in agregate leverage that are associated with credit supply shocks.

The rest of the paper is organized as follows. Section 2 discusses the related empirical literature on the consequences of bank capital shocks for credit and growth, and highlights shortcomings of existing approaches. Section 3 explains the modelling strategy. Section 4 presents our selection of banks and our macroeconomic databases. Section 5 details the model specifications and presents the estimation procedure. Section 6 discusses the results. Finally, section 7 concludes.

2 Related literature

As mentioned earlier, researchers have long been interested in assessing the economic consequences of fluctuations in credit supplied by banks. In particular, the main historical

[5] Cf. Kashyap, Stein and Wilcox (1993) on the financing mix of firms, as well as, more recently Adrian, Colla and Shin (2011). The latter suggest that during the finnancial crisis of 2007-2009, bond financing made up for almost all the reduction in bank lending to large US firms.

episodes of severe recessions associated with falling bank credit, bank capital depletion and bank failures, like the recent crisis, the Great Depression of the 1930s, the US recession of the early 1990s and Japan's "lost decade" in the late 1990s-early 2000s, each time motivated new waves of empirical contributions aiming to overcome some of the well-known identification challenges that impede any assessment of the causal impact of bank capital shocks on loan supply and activity.[6]

Against this background, our paper relates first to a strand of empirical studies that look for new aggregate indicators to be included in small monetary VARs or even univariate regressions in order to better identify credit supply shocks. These indicators are intended to provide independent information on bank credit supply and thus help to disentangle demand and supply effects in the fluctuations in observed reduced-form credit aggregates. A first example is provided by Peek, Rosengren and Tootel (1999, 2003), who take advantage of confidential supervisory information collected by the US Fed to construct an aggregate indicator of banks' financial health, defined as the share of assets held by banks falling into the "CAMEL 5" bucket (i.e. viewed by the regulator as likely to fail in the coming quarters). They notably show that their bank health indicator predicts unemployment and inflation one year ahead and provide evidence that shocks to this indicator do reflect shocks to credit supply. Morgan (1998) suggests looking rather at the share of loans under commitment out of total loans, since the former will be less affected by a voluntary contraction in lending by banks than loans without pre-agreed commitments. Lastly, Lown and Morgan (2006), for the US, and Ciccarelli et al. (2010), for the euro area, show that indexes of lending standards, as constructed by central banks from individual answers to loan officer surveys on loan conditions, are useful proxies of credit supply. In the same vein, but using a bottom-up methodology closer to ours, Basset et al. (2011) construct an aggregate summary series of bank-level innovations to lending standards and use it as an exogenous series of shocks to bank credit supply in a small monetary VAR of the US economy. Measures of credit supply building on bank lending surveys indeed look particularly promissing, since by construction, and to the extent that the answers given by bankers are deemed trustworthy, the decomposition between developments in credit demand and supply is given. However, none of these various measures of credit supply are directly related to the capital position of banks. As such, they may recflect binding capital constraints as well as liquidity shortages, or any other sources of credit supply contractions or expansions (like a change in business

[6]See, among others, Bernanke (1983), Bernanke and Lown (1991), Woo (2003), Berrospide and Edge (2010).

strategy, for instance).

The panel regression which corresponds to the second step in our estimation strategy follows on several papers using bank-level regressions to gauge the effects of bank capital (more precisely bank leverage) on lending (see, e.g., Hancock and Wilcox, 1994, Kashyap and Stein, 2000 or Berrospide and Edge, 2010). Recently, some researchers have argued that microeconomic bank-level data alone are insufficiently precise to allow for a correct identification of the causal impact of bank balance sheet shocks on credit supply and economic activity (see Peydro, 2010, for a survey). Indeed, not only is aggregate credit demand or borrower quality often correlated with aggregate credit supply, but there may be also a correlation in the cross section. For instance, if poorly capitalized firms that need more bank funding in bad times tend to match with lowly capitalized banks (as is documented in the Japanese case by Caballero, Hoshi and Kashyap, 2008), estimates of the true negative effects of bank capital contraction on lending will be biased downwards because lowly capitalized banks will face a countercyclical increase in loan demand for which there is no way to control using bank fixed effects alone. As a consequence, several recent studies have used large loan-level datasets (taken from the credit registers held by the central banks of some countries), either in panel regressions with firm-bank fixed effects or in diff-in-diff setups, in order to investigate afresh a series of standard issues in empirical banking or assess the consequences of shocks to bank balance sheets on loan supply during the recent crisis (cf. e.g. Khwaja and Mian, 2008 and the references cited in Peydro, 2010). However, it is fair to note that, while papers along this line are obviously very successful in identifying credit supply effects, they have little to say about the aggregate consequences and fail to account for general equilibrium effects. By construction, a diff-in-diff approach is indeed suitable for highlighting how cross-sectional heterogeneity in the situation of banks helps to understand different lending behaviour in relative terms, but not for assessing the aggregate effects in absolute terms. Besides, in such frameworks, there is no way to look at feedback effects from the macroeconomy to the bank balance sheets.

Last but not least, our study fits into a very recent literature that uses dynamic factor models in order either to better identify financial shocks and assess their impact on a number of macroeconomic aggregates or to jointly exploit the information contained in both large microeconomic bank balance sheet datasets and small or large macroeconomic databases. Looking at credit shocks defined as exogenous increases in corporate spreads, Gilchrist et al. (2010) and Boivin et al. (2009) are two examples of papers exploring the first avenue. Daves et al. (2010), Buch et al. (2011) and Jimborean and Mesonnier (2010) are some of the few available studies investigating the second.

3 Modelling strategy

We outline in this section our modeling approach in four steps:

1. Using a dynamic factor model, we first extract a vector of non-bank macro shocks, η_t, from a large macroeconomic database X that gathers series related to real activity, prices, and market interest rates, but excludes any credit or money indicator;

2. using the estimated $\widehat{\eta}_t$ as controls, we run standard panel regressions of individual bank capital ratios on banks specific and macroeconomic determinants. We thus obtain a panel of estimated exogenous innovations to individual bank capital ratios, denoted $\widehat{\varepsilon}_{i,t}$;

3. We aggregate the bank-specific $\widehat{\varepsilon}_{i,t}$ into a macroeconomic measure of exogenous shocks to capital ratios, $\widehat{\varepsilon}_t$;

4. Finally, we compute impulse response functions (IRFs) of the macro variables of interest in X to aggregate capital ratio shocks $\widehat{\varepsilon}_t$ using the FADL approach. Note that the flexibility of this approach allows us to also compute IRFs of ancillary macro variables that are not in X, like credit aggregates or bank lending rates.

3.1 Estimation of macroeconomic shocks

The first step of our approach aims to estimate a vector of "non-bank related" macroeconomic shocks that we can then use as controls in the panel regressions of the second step, when we model the dynamics of bank capital ratios at the bank level. We extract these macro shocks from a large database of macro series using a factor method. The database encompasses many macroeconomic measures of real activity, prices, interest rates of different maturities and some measures of financial conditions (as corporate bond spreads and broad stock market index returns), but no money or credit variables. Conceptually, the selection of the series in this macroeconomic database is thus in line with standard reduced-form general equilibrium models of the US economy which feature three equations for activity (IS curve), inflation (Phillips curve) and the monetary policy rate (Taylor-like rule).

Let thus X be the chosen $T \times N$ dataset of macroeconomic aggregated series representing the US economy. Note here that all series are stationary or have been transformed in order to be covariance stationary. We assume that X_t allows for a general dynamic factor representation:

$$\begin{aligned} X_t &= \lambda(L) f_t + u_t & (1)\\ u_t &= D(L) u_{t-1} + v_{Xt} & (2)\\ f_t &= \Gamma_1(L) f_{t-1} + \Gamma_0 v_{ft} & (3) \end{aligned}$$

where f_t contains q common factors that evolve as a vector autoregressive (VAR) process of order h, $\lambda(L)$ is a polynomial matrix of factor loadings of order s, $D(L)$ is a diagonal polynomial matrix, v_{Xt} is a vector white noise process, v_{ft} is a vector of q structural shocks such as demand, supply or monetary policy. We assume that the characteristic roots of $\Gamma_1(L)$ are strictly less than one, $E(v_{Xit}v_{Xjt}) = 0$, and $E(v_{Xit}v_{fkt}) = 0$ for all $i \neq j$ and for all $k = 1, \ldots q$.

Remember that the goal of this first step is not to identify the underlying structural shocks v_{ft}, but merely to control for all of them simultaneously when estimating the leverage shocks at the bank level, as we explain in details below. Hence, we only need to estimate the space they span, that is the vector of reduced-form innovations: $\eta_t = \Gamma_0 v_{ft}$.

3.2 A dynamic model of bank leverage targeting

The second stage of our analysis consists of estimating a dynamic model of bank capital-to-asset ratios in order to retrieve a panel of exogenous shocks to the capital ratios at the individual bank level. For this purpose, we follow Hancock and Wilcox (1994), among others, and assume that because of some unspecified costs to capital adjustment banks cannot immediately adjust their capital ratio towards their (time-varying) target.[7] The change in the capital ratio in each period thus depends on the gap between the target and actual capital ratios in the previous period and on an exogenous shock:

$$k_{i,t} - k_{i,t-1} = \lambda \left(k^*_{i,t-1} - k_{i,t-1}\right) + e_{i,t} \tag{4}$$

where $k_{i,t}$ is the actual capital ratio at (the end of) period t for institution i, $k^*_{i,t}$ is the target capital ratio, λ a parameter driving the speed of adjustment and $e_{i,t}$ a bank-specific innovation to leverage. As is standard, the target capital ratio is in turn assumed to be a linear function of bank-specific characteristics, stacked in a vector $Z_{i,t}$, and a set of macro variables, $M_{i,t}$, so that $k^*_{i,t} = \theta_Z.Z_{i,t} + \theta_M.M_{i,t}$. The motivation for choosing

[7]For recent examples of this approach, see e.g. Berrospide and Edge (2010) and Francis and Osborne (2012).

both sets of variables is the assumption that they belong to the informational basis that bank officials routinely monitor when they decide on the "optimal" target ratio for their specific institution. In particular, the macro variables chosen should reflect sources of macro risks that bankers would take into account in their capital policy. Note that, although the innovations $e_{i,t}$ are exogenous to the macro variables stacked in $M_{i,t-1}$ by construction, they may not be orthogonal to macroeconomic shocks occurring between $t-1$ and t, such as an exogenous real demand shock or an exogenous monetary policy shock. For instance, a negative monetary policy shock that would imply a rise in the short-term rate during period t would tend to curtail banks' profits, and hence affect their capital through a lower (or even negative) accumulation of earnings. Let us suppose, as we do in section 3.1 above, that observed fluctuations in a large set of macroeconomic variables relevant for describing the state of the economy can be subsumed to the propagation of a small number of unobserved common shocks, which are not explicitly related to the state of the banking sector. Extracting truly structural shocks to individual banks' capital ratios then entails also controlling for the space spanned by these structural macroeconomic shocks, that is to say controlling for the vector of reduced-form common shocks η_t obtained from the first step.

Replacing in equation 4, rearranging and adding a bank-specific fixed effect, we finally get our estimation equation for the bank capital ratio:

$$k_{i,t} = \alpha_i + (1-\lambda).k_{i,t-1} + \lambda.\theta_Z.Z_{i,t-1} + \lambda.\theta_M.M_{t-1} + \theta_\eta.\eta_t + \varepsilon_{i,t} \tag{5}$$

The residuals $\varepsilon_{i,t}$ can now be interpreted more convincingly as exogenous shocks to individual bank capital ratios. Note that these may still reflect a variety of circumstances: changes in the regulatory environment and changes in the specific requirements imposed by the regulator on a given bank are of course of the essence, but changes in the business model or risk strategy of the bank (following e.g. the appointment of a new CEO) and leverage adjustments due to unexpected windfall profits and losses on some assets (which may not be spanned by the vector of economy-wide macro shocks extracted above) may also show up. However, by construction, the $\varepsilon_{i,t}$ should no longer reflect the impact on bank leverage of other macroeconomic shocks that may also drive the business cycle, such as productivity, real demand or monetary policy shocks. Note that to the extent that a substantial part of of the fluctuations of variables in X may be driven by credit supply shocks, such shocks may be captured by our estimated η_t. By controlling for η_t we are thus quite conservative against our assumption that pure bank leverage shocks matter for explaining macroeconomic fluctuations.

3.3 Aggregation

To obtain an aggregate series of exogenous shocks to large banks' capital ratios, $\widehat{\varepsilon}_t$, we then compute a weighted average of the residuals for the banks present in our panel in each period:

$$\widehat{\varepsilon}_t = \sum_{i=1}^{\widetilde{N}_t} a_{i,t-1}.\widehat{\varepsilon}_{i,t}$$

where $a_{i,t-1}$ denotes the share of bank i at period $t-1$ in the total assets of the $\widetilde{N}_t = \min(N_t, N_{t-1})$ institutions present in the sample. Weighting the individual residuals by a measure of the relative size of the banks is of the essence since we aim to construct a measure that is macroeconomically meaningful: intuitively, the macro consequences, if any, of a leverage shock to a bank totaling \$ 200 billion should not be the same as of a shock to a bank holding less than \$ 10 billion.[8] Note that we take the lagged share of total banking assets as weights, instead of the contemporaneous share, because the size of the bank in a given period is obviously endogenous to the leverage shock received within that period.[9]

3.4 Impulse response analysis

Last, we implement the Factor-Augmented Distributed Lag (FADL) approach recently proposed by Ng and Stevanovic (2012) in order to estimate the impulse response coefficients of macro variables of interest to the aggregate bank leverage shock. Once we have estimated the space spanned by the common macroeconomic shocks, η_t, and the leverage shock, ε_t, the idea of the FADL methodology is to augment an autoregression of a variable of interest, y_t, with current and lagged values of the estimated shocks $\hat{\eta}_t$ and $\hat{\varepsilon}_t$:

$$y_t = \alpha_y(L)y_{t-1} + \alpha_\eta(L)\hat{\eta}_t + \alpha_\varepsilon(L)\hat{\varepsilon}_t + v_{yt}. \tag{6}$$

[8] Following the methodology of Gabaix (2011), Buch and Neugebauer (2011) compute "granular banking residuals" for a panel of industrial economies including the US, and find that idiosyncratic changes in the volume of credit granted by the few largest banks matter for explaining business cycle fluctuations.

[9] Of course, as our panel is unbalanced, this weighting scheme entails that some pure composition effects may affect the aggregate shock constructed. However, since we impose that banks stay in the panel for at least 32 periods and most banks indeed stay for a much longer period of time, we may assume that these composition effects remain small. Indeed, we have constructed an alternative aggregate series of shocks weighted by the contemporaneous asset shares and checked that our results remained qualitatively unchanged.

Let first suppose that y_t belongs to the dataset X_t initialy used to estimate the "non-bank macro" shocks η_t.If $y_t \in X_t$, its FADL representation is derived from the dynamic factor model (1)-(3), given that $D(L)$ is a diagonal matrix polynomial:

$$y_t = \delta_y(L)y_{t-1} + (1-\delta_y(L))\lambda_y(L)(I-\Gamma(1)L)^{-1}\eta_t + v_{Xyt}, \tag{7}$$

and augmented by $\alpha_\varepsilon(L)\varepsilon_t$. Since η_t and ε_t are not observed, we replace them by their estimates. If the leverage shock is important for y_t, the corresponding coefficients should be significant.

To construct the impulse responses, we estimate equation (6) by OLS. The dynamic responses of y_t to a unit increase in $\hat{\varepsilon}_t$ are defined by

$$\hat{\psi}_y^\varepsilon(L) = \frac{\hat{\alpha}_\varepsilon(L)}{1-\hat{\alpha}_y(L)L}.$$

Since $\hat{\alpha}_y(L)$ is a scalar rational polynomial, the impulse response coefficients are easy to compute using the FILTER command in MATLAB. Note that imposing restrictions on FADL impulse response functions is very easy. For example, to constrain the impact response of y_t to $\hat{\varepsilon}_t$, it is sufficient to restrict $\alpha_\varepsilon(0) = 0$. In principle, any linear regression restriction can be imposed to shape the impulse response functions of interest.

This approach is very appealing in our context for several reasons. Firstly, the identification of the shock of interest, ε_t, is done at the micro-level in such a way that $\widehat{\eta}_t$ and $\widehat{\varepsilon}_t$ are orthogonal by construction. Hence we do not have to deal with any of the rotation and identification issues that normally occur within the FADL framework as well as in standard FAVARs, as discussed at length in Ng and Stevanovic (2012). The previously estimated leverage shock is simply added to the FADL representation of y_t and we only need to pin down its standard deviation. Secondly, y_t does not need to be in X_t. We can estimate FADL regressions for any variable, and test if it has a factor structure and if it responds to the leverage shock. As a matter of fact, in the following, we estimate additional FADL regressions for a selection of credit and banking indicators stacked in an ancillary dataset Y, which, as detailed in the following section, does not belong to the set of variables in X used for the extraction of common macro shocks.

Last but not least, it is important to note that, with the FADL approach, restrictions on the responses of the variables in X_t or Y_t, if required by the theory, can be imposed equation by equation. Restrictions imposed on the IRF of one series thus would not impinge on the IRF of another one, and would not affect the estimation nor the identification of structural shocks. That said, we wish here to take an agnostic stance regarding the consequences of bank leverage shocks for the macroeconomy and thus do not impose any restriction to the impulse responses of the macro variables of interest.

4 Data

A specific feature of our approach is that we use both panel regression techniques on bank-level data and a time series analysis of macroeconomic variables in a data-rich environment. In this section, we thus describe at length these different datasets.

4.1 Constructing a database of large US banks

Our source of bank balance sheet information is the Consolidated Financial Statements for Bank Holding Companies (FRY-9C) collected by the US Federal Reserve (the "Call reports"). We consider bank balance sheet information at the level of the Bank Holding Companies (BHCs) instead of the level of the commercial banks that belong to these groups, because decisions regarding the choice of the targeted leverage of an institution are arguably taken at the level of the bank holding or bank group and not necessarily at the level of the subsidiaries.[10] In the following, we use the generic term "banks" to denote the BHCs in our sample. Our bank database covers the period from 1986 Q1 to 2010 Q1. Notably, the period of study thus covers the years of implementation of the first Basel capital regulations (post 1988), the "credit crunch" episode of the early 1990s, the IT-boom and bust and the recent subprime crisis, i.e. several time spells in which we can expect large shocks to bank leverage to have happened with potentially significant macroeconomic consequences.

As in many developed economies, the US banking system has experienced a large wave of mergers and acquisitions since the late 1980s. As a consequence, the total population of bank holding companies as recorded in the initial balance sheet database shrank to 236 in 2010 from more than 330 back in 1986. Besides, the raw database is highly unbalanced, with 819 different institutions identified, out of which only 66 are present throughout the sample period. Finally, a major statistical break occurs in 2006 Q1, when a change in the reporting guidelines stated that subsidiaries with total assets of more than one billion USD were no longer required to file a separate reporting. Because of 32 institutions fell into this category and stopped their reporting at this date, the total cumulated assets of the

[10] Houston, James and Marcus (1997) and Houston and James (1998) find that loan growth among affiliated banks is more sensitive to the cash flows and capital position of their holding company than it is to their own, and that it is less sensitive to their own capital position relative to unaffiliated banks. Overall, their results suggest that bank holding companies develop internal capital markets to allocate capital among their subsidiaries.

reporting banks dropped by some 30% in early 2006.

Taking these features of the initial balance sheet database into account, we designed our selection of institutions in order to meet a few simple criteria. First, we want to focus on the largest US bank corporations, expected to have relatively similar leverage behaviors, so running a panel regression on our set of institutions would make sense. We thus kept only the banks whose total assets always remained above \$ 3 billion.[11] Second, we were concerned about limiting the selection bias due to the attrition of the database over time, while ensuring some minimal degree of stability through time of the selected sample of banks. We thus excluded institutions with missing observations of total assets and equity capital and also banks that remain in the sample for less than thirty-two quarters. Third, we deleted bank subsidiaries affected by the change in reporting guidelines mentioned above so as to avoid any double counting.

As said, a large number of mergers and acquisitions have affected the US banking system since the mid-1980s. We used the Chicago Fed database on M&A involving BHC to identify bank-quarter observations when such operations took place. Some 356 M&As happened in our sample, compared to more than 9,600 for the whole BHC population. Contrary to the practice in many bank panel studies, we do not reconstruct merged banks backwards. Nor do we rename the acquiring banks from the acquisition date onward, because this would lead to too many large banks with a too small number of consecutive observations. Instead, we deal with M&As by including a dummy in the panel regressions presented below.

Our sample finally consisted of 104 large BHCs that represent on average 75% of the total assets in the US banking sector.[12] Figure 1 shows the share of the selected institutions out of total US banking assets through time. Although the representativeness of our sample varies somewhat (between 60 percent and 80 percent of the total), it remains sufficiently high throughout compared to similar studies. Note that of the 104 selected institutions only 20 remain present over the whole sample period.

4.2 A rich macroeconomic dataset

In this paper, we use a large number of macroeconomic series for two joint purposes. First, using a factor model as presented in section 3.1, we want to uncover the space spanned by real and nominal structural shocks, other than shocks originating from the banking sector, that may also drive part of the fluctuations in bank capital ratios. Second, we want to

[11] This corresponds roughly to the 55th percentile of banks ranked according to their average total assets over the period 1986-2010.

[12] Please see the Appendix for the complete list of banks in our selection.

be able to ultimately compute the responses of a wide array of aggregate variables to our estimated bank leverage shocks. We describe here the collection of macroeconomic time series that we use throughout.

A huge number of time series of aggregate variables representing the US economy are available to the econometrician for analysis (see e.g. Stock and Watson, 2002, and Bernanke et al., 2005 for examples of studies using several hundreds of variables). However, selecting only a few dozen of them may be enough for our purpose, as in Gilchrist et al. (2009). Indeed a factor structure may not be appropriate for every series. If the additional data are noisy, uninformative and/or do not satisfy the restrictions of the factor model, it may not be useful to consider them when estimating the common shocks, as shown in Boivin and Ng (2006).[13]

Hence, we construct here two separate macroeconomic datasets. The first one, denoted by X, is a comprehensive sample of thirty-one aggregate variables representing a large variety of real and nominal measures of the state of the US economy, but excluding any money and credit aggregates or other possible indicators of banks' credit supply behavior (like surveys on credit conditions). This sample is used to extract the common macroeconomic shocks η_t that we take as controls when we estimate the bank capital ratio shocks. The second macroeconomic dataset, denoted by Y, encompasses a list of aggregate credit and banking indicators that are not included in X.

The variables included in X can be classified into four broad categories: economic activity indicators, inflation indicators, risk-free interest rates, and other financial indicators or asset prices. All series are observed at quarterly frequency and transformed to stationarity before we apply the factor analysis (cf. Appendix A for details of data sources and transformations to stationarity applied to individual series).

The selection of real and nominal macro variables partly follows Gilchrist et al. (2010). In particular, we consider the following twelve indicators of economic activity (with quarterly frequency): (1) the capacity utilization index; (2) real GDP; (3) private domestic investment; (4) the industrial production index; (5) the Institute for Supply Management (ISM) diffusion index of activity in the manufacturing sector; (6) non-farm payroll employment; (7) real personal consumption expenditures (PCE) ; (8) real PCE in durable goods; (9) real PCE in non-durable goods; (10) the civilian unemployment rate; (11) the Conference Board's coincident business cycle indicator index; and (12) housing starts.

[13] Note however that the FADL analysis we implement here only requires a strong factor structure to hold in the macroeconomic dataset and is less likely to be affected by the presence of weak factors in very large data sets as noted in Onatski (2009).

Price developments are summarized by the following seven inflation indicators: the log-difference of (1) the Consumer Price index (CPI); (2) the core CPI; (3) the Producer Price index (PPI) for all commodities; (4) the PPI for finished goods only (core PPI); (5) the CRB index of (spot) commodity prices; (6) the price of oil as measured by the price per barrel of West Texas Intermediate (WTI) crude; (7) the price of imported goods.

Our broad macroeconomic dataset also includes the entire term structure of interest rates, starting at the short end with the effective federal funds rate and continuing with the constant maturity Treasury yields at 6-month, 1-year, 2-year, 3-year, 5-year, and 10-year horizons, for a total of seven interest rates.[14]

Finally, we also include five series of asset prices that we deem relevant for understanding business cycle fluctuations in the US since the late 1980s: (1) the nominal effective exchange rate of the US dollar against a basket of major currencies; the spread of (2) AAA and (3) BAA corporate bond yields over ten year Treasuries; (4) the S&P 500 equity index and (5) the FHFA housing price index.

Regarding the additional dataset of credit and banking indicators stacked in Y, we consider the following series: (1) total commercial bank credit; (2) commercial and industrial (C&I) loans; (3) consumer loans; (4) real estate loans; (5) loans and leases in bank credit; (6) total bank deposits; (7) total bank assets of commercial banks; (8) total loans by banks and thrift corporations. All these series are taken from the H8 statistical release of the Federal Reserve (Assets and Liabilities of Commercial Banks in the U.S), except the last one (which comes from the Z1 release). In addition, we also consider (9) credit standards, as taken from the Senior Loan Officer Survey on credit conditions conducted by the Federal Reserve (a rise in the indicator denotes a tightening of credit conditions to firms); and (10) the aggregate measure of the leverage of the US commercial banking sector as used in Berrospide and Edge (2010). This leverage ratio is computed by the Fed on the basis of individual Call reports as the ratio of the sum of all commercial bank equity to the sum of all banks' assets.[15] Although we think this is an inaccurate measure of aggregate bank leverage, we include it in our selection for comparison purpose. Last, in order to better gauge whether or not our identified leverage shock is akin to a credit supply shock, we include several series of credit interest rates: (11) interest rates on personal loans with maturity up to two years, (12) rates on new car loans with maturity up to 4 years, both

[14] Although nominal yields exhibit a discernible downward trend over our sample period (1986–2008), they are not converted into real terms so as to ensure their approximate stationarity as in Gilchrist et al. (2010). Indeed, since we extract the factors by iteratred principal components on prewhitened macro series, the strong persistence of interest rate series is not an issue.

[15] The series is available from the US Fed FRED database with code EQTA.

taken from the Survey on consumer credit (G19 release), and measures of (13) average rates on all C&I loans, (14) on large C&I loans (above \$1 million) and (15) on small C&I loans (below \$100 thousand). The latter interest rates series on loans to firms are extracted from the Survey of terms of business lending (E2 release).

5 Estimation and results

5.1 Estimation of the dynamic factor model

To extract an estimate of the macroeconomic shocks η_t that drive the common fluctuations of the variables in X_t, we implement an algorithm that builds on the iterative principal components (IPC) approach of Stock and Watson (2005). This method is briefly summarized below.

The starting point is the static factor representation of the pre-whitened data $x_t = (I - D(L)L)X_t$ in equations (1-3):

$$\begin{aligned} x_t &= \Lambda F_t + v_{Xt} &(8)\\ F_t &= \Phi_F F_{t-1} + \epsilon_{Ft} &(9) \end{aligned}$$

where $\epsilon_{Ft} = G\eta_t$, Λ is the $N \times r$ matrix of loadings, F_t is $r = q(s+1) \times 1$ with

$$\Lambda = \begin{pmatrix} \Lambda_1 \\ \Lambda_2 \\ \vdots \\ \Lambda_N \end{pmatrix}, \qquad F_t = \begin{pmatrix} f_t \\ f_{t-1} \\ \vdots \\ f_{t-max(h,s)} \end{pmatrix}, \qquad \Phi_F = \begin{pmatrix} \Gamma_1 & \Gamma_2 & . & . & . & \Gamma_s \\ I_q & 0 & . & 0 & . & 0 \\ 0 & I_q & & 0 & . & 0 \\ . & 0 & & . & . & 0 \\ 0 & 0 & . & I_q & . & 0 \end{pmatrix} \qquad \Lambda_i = \begin{pmatrix} \lambda_{i0} & \lambda_{i1} & \dots \lambda_{is} \end{pmatrix}$$

and G is an $r \times q$ matrix that maps the dynamic shocks into the static shocks. The ϵ_{Ft} are the reduced form errors of F_t and are themselves linear combinations of the structural shocks v_{ft}. The algorithm then proceeds in three steps:

Step 1: First, we estimate F_t by iterative principal components (IPC) as in Stock and Watson (2005).

1.i Initialize $\delta_i^X(L)$ using estimates from a univariate AR(q) regression in X_{it}. Let $D(L)$ be a diagonal matrix with $\delta_i^X(L)L$ on the i-th diagonal.

1.ii Iterate until convergence

$$\min_{D(L),\Lambda,F} SSR = \sum_{t=1}^{T} \Big((I - D(L)L)X_t - \Lambda F_t \Big)' \Big((I - D(L)L)X_t - \Lambda F_t \Big).$$

1.ii.a Let $\hat{F}_t$ be the first k principal components of xx' using the normalization that $F'F/T = I_k$, where k is the assumed number of static factors.

1.ii.b Estimate $D(L)$ and Λ by regressing X_{it} on $\hat{F}_t$ and lags of X_{it}.

Step 2: Second, we estimate a VAR in $\hat{F}_t$ to obtain $\hat{\Phi}_F$.

Step 3: Last, we estimate η_t:

3.i Let $\hat{\epsilon}_{Xit} = x_{it} - \hat{\Lambda}_i' \hat{\Phi}_F \hat{F}_{t-1}$, where $\hat{F}_t$ are the iterative principle components of all n observations of the panel x, $\hat{\Lambda}$ and $\hat{F}_{t-1}$ and $\hat{\Phi}_F$ are obtained from Step (1).

3.ii The estimate of η_t consists of the first q principal components of $\hat{\epsilon}_{Xit}$.

Step (3) is based on the fact that $v_{it} = x_{it} - \Lambda_i F_t = x_{it} - \hat{\Lambda}_i(\hat{\Phi}_F F_{t-1} + \epsilon_{Ft})$. Let us now define

$$\begin{aligned}\hat{\epsilon}_{Xit} &= x_{it} - \Lambda_i \Phi_F F_{t-1} \\ &= \Lambda_i \epsilon_{Ft} + v_{it} \\ &= (\Lambda_i G)\eta_t + v_{it}.\end{aligned}$$

As noted in Stock and Watson (2005), the rank of the $r \times 1$ vector ϵ_{Ft} is only q, since F_t is generated by q common shocks. In other words, $\hat{\epsilon}_{Xit}$ itself has a factor structure with common factors η_t. Amengual and Watson (2007) show that the principal components of $\hat{\epsilon}_{Xt}$ can precisely estimate the space spanned by v_{ft}. In practice, the dimension of η_t, q, is unknown and must be chosen by the econometrician, if possible on the basis of some statistical tests. In the case of our application, we follow the standard information criteria proposed by Bai and Ng (2007) and Amengual and Watson (2007) and set the number of common shocks to $q = 3$.

Note that, since usual tests confirm that three shocks are sufficient to describe the bulk of the correlations present in X with a small-scale dynamic factor model, then we may be confident that we have extracted all possible real demand and supply shocks spanning business cycle fluctuations (up to a rotation). Since our dataset also includes various measures of prices and short- and long-term interest rates and there is little doubt that the short-term interest rate is an appropriate measure of the stance of monetary policy in the US over the period of our study, we may also be quite certain that monetary policy shocks will be also properly accounted for by these three series of shocks.

5.2 Estimation of the panel regression

We present in this section the results from the estimation of the bank-level regression (5), that we repeat here for convenience's sake:

$$k_{i,t} = \alpha_i + (1-\lambda).k_{i,t-1} + \lambda.\theta_Z.Z_{i,t-1} + \lambda.\theta_M.M_{t-1} + \theta_\eta.\widehat{\eta}_t + \varepsilon_{i,t} \tag{10}$$

The bank-specific variables stacked in $Z_{i,t}$ include a measure of bank size (the log of total assets), a measure of bank profitability (the return on assets, or ROA), a measure of asset risk (the ratio of net-charge-offs to assets), and two measures of asset structure (the ratio of mortgage loans and the ratio of commercial and industrial loans to assets). The first three are standard determinants of bank capital ratios in the empirical literature. The relative shares of real estate loans and loans to firms in bank assets may be viewed as additional proxies for bank risk, at least through the lense of the first Basel capital regulations which imposed weighting C&I loans more than mortgage loans in the computation of regulatory capital requirements. Alternatively, these simple measures of asset composition may help to capture some specialization of individual banks. Last, two sets of bank-specific dummy variables are also included as regressors. First, we add bank-specific dummies that take the value of one in quarters when the bank has acquired another institution. Second, we also add dummies capturing a change in status from BHC to Financial Holding Company (FHC). Indeed, an important institutional change for US banks since 1986 was the adoption of the Gramm-Leach-Bliley Financial Services Modernization Act of 1999 (GLB Act). This relaxed the provisions of the 1933 Glass-Steagall Act requiring a strict separation of banking and securities activities. Under the new legislation, BHCs that meet some supervisory standards are allowed to become FHCs. Switching to the FHC status authorizes a bank to engage in a range of new financial and non-financial activities, possibly affecting both its business model and its level of risk. Again using information provided by the National Information Center on US financial institutions run by the Federal Reserve, we identified 27 changes from BHC to FHC status and 8 changes back to BHC status in our selection of banks and we created a dummy variable taking the value of one for observations under FHC status.

Table 1 reports summary statistics for the bank-specific variables used in the panel regressions. The median institution in our sample is already quite large, with assets above $ 19 billion.[16] Nevertheless, some substantial degree of heterogeneity in size remains in the sample, as the four largest institutions have average assets above $ 400 billion, while the

[16] For comparison, the median BHC in the sample used by Berropside and Edge (2010) has assets around $ 3 billions only.

smallest ones have average assets below \$ 5 billion. The distribution of variables scaled by assets is however more homogenous, be it capital, loans or net charge-offs. The average capital ratio is slightly above 8 percent, which corresponds to a leverage of about 12.5 for the average bank. Overall, loans to non-financial clients make up more than 60 percent of the total in the average bank's balance sheet, with mortgage loans representing in turn about 40 percent of all loans. Average profitability, as reflected by our measure of ROA, is 2.59 percent, which is broadly in line (but a little lower) with the average ROA for all US commercial banks over the same period of 25 years.[17] Net charge-off rates, which we take as a proxy for the riskiness of bank assets, are also of the order of magnitude of the available aggregate statistics for the whole US banking system. Appendix A provides details of data sources and the definitions of these variables.

Assuming that banks choose their target capital ratio in order to absorb expected future losses on their assets, any macroeconomic information that is deemed relevant to their gauging the probability of future losses should also be included in our regression. Indeed, the ratio of net charge-offs alone mainly reflects the perceived consequences of current and past adverse shocks and is rather backward-looking in nature. We consider here two types of macro control variables in the M_t vector. First, we take the log of the Chicago Board VIX as a measure of uncertainty on the US equity market. Second, we take the expectations of two key macroeconomic indicators at a one-year horizon, as collected by the Survey of Professional forecasters conducted by the Philadelphia Fed. These two measures of macroeconomic expectations relate to: (1) the expected variation in the short-term rate of interest (the rate on 3 month T-Bills), (2) the expected rate of growth of real GDP. Table 2 provides some descriptive statistics for this first set of macro controls. Last but not least, we include in the regression our estimate of the common macroeconomic common shocks stacked in $\widehat{\eta}_t$.

Table 3 presents the estimation results of equation 5. A constant and three seasonal dummies are included in the regression but not reported for brevity. We estimate the dynamic model of bank leverage using OLS with bank fixed effects as suggested by preliminary Hausman tests, and t-stats are computed using the Huber-White robust estimator of variance.[18] Although it is well known that the estimation of a dynamic panel with fixed effects entails the possibility of biased OLS estimates, we rely on the simulation results in Judson

[17] The average ROA for all US commercial banks (on an unconsolidated basis) is close to 4 percent over 1986-2010.

[18] Correcting the variance for possible within-correlation at the individual level (clustering) does not make any difference.

and Owen (1999), who suggest that this bias drops quickly to zero when the time dimension of the panel is long enough (more than 30 periods). Since individual banks in our selection are present on average for 59 periods and always for more than 30, we conclude that a GMM approach is not required here.

The first column of Table 3 presents the results when only bank-specific variables are included as regressors. Columns 2 to 4 show the impact of also including observable macroeconomic variables, like macro expectations, common shocks extracted from the dataset in X using a dynamic factor model, or both. The full specification in column 4 is our baseline model in the following.

Whatever the specification, the large coefficient we obtain for the lagged capital ratio confirms the well-known fact that bank book capital to asset ratios are very persistent at the institutional level. This implies that the remaining regressors will account for only a modest share of total variance. Nevertheless, we choose to model the level and not the first difference of the ratio, for two reasons: first, although persistent, capital ratios are by nature bounded variables, and the economic rationale for assuming that they follow an integrated process is not clear; second, interpreting the response of macroeconomic variables to a bank leverage shock as we do below is more intuitive if we construct our aggregate capital shock series on the basis of innovations to the levels of the individual ratios, not to the changes in them.

Looking at the role of other bank-specific covariates, we find a positive correlation between capital ratios and asset sizes, in line with previous results of Berrospide and Edge (2010), who also restrict their sample to the largest US BHC. This contrasts, however, with the results from studies based on larger populations of US commercial banks, including small ones, which suggest that small banks on average keep higher capital buffers than large ones.[19] Nevertheless, the standard asymmetric information argument that provides a rationale for this stylized fact of better capitalized small banks may not be very relevant for the population of large listed BHCs that we look at in this study. Past profitability of assets (lagged ROA) does not turn out to be significant, but (lagged) net charge-offs are positively correlated with capital ratios, confirming the intuition that bank managers adjust their capital ratio to compensate for the capital depletion that would eventually follow a degradation in the quality of assets. Mergers and acquisitions are associated with a significant increase in the capital ratio, but a switch to FHC status does not have any noticeable impact.

[19] Cf. for instance Kashyap and Stein (1995) and Kishan and Opiela (2000).

The observable macroeconomic controls included are all significant, suggesting that their omission would bias our analysis. As in Berrospide and Edge (2010), a higher volatility in stock markets tends to imply a lower capital ratio, which may reflect higher losses in times of stress. An expected rise in GDP growth is associated with a decrease in capital ratios, which hints at a procyclical behavior of bank leverage. Meanwhile, expected policy rate hikes over the following year are associated with an increase in the current capital ratio, which suggests that this variable can be seen as a "risk factor" impinging on the expected profitability of assets. Finally, at least one of the lagged common shocks summarizing the perceived state of the economy emerges as significant, but at the expense of the expected GDP growth regressor, suggesting that this estimated structural macro shock accounts for a large proportion of aggregate GDP fluctuations.

5.3 Aggregate measure of bank capital ratio shocks

Figure 2 shows the aggregate series of capital ratios shocks we obtain for the US banking system. The series has a mean close to zero and a standard deviation of 0.2 percentage points. According to our measure, the largest negative shocks occurred in the second quarter of 1987, the third quarter of 1989, the first quarter of 1994, the first quarter of 2005, and then, during the last recession, in the first semester of 2007 as well as, in the aftermath of the Lehman failure, the third quarter of 2008. Large positive shocks to bank capital ratios occured at the end of 2000, just at the onset of the recession triggered by the burst of the dotcom bubble, and also in the third quarter of 2004 and, last but not least, in early 2009, possibly as a consequence of the TARP program and the ensuing forced recapitalization of US banks during 2009.

Note that the panel regression (5) assumes that all banks react in a homogenous way to bank characteristics, as is commonly assumed, but also to the macro shocks η_t. This last assumption may seem at odds with the findings of Buch, Eickmeier and Prieto (2010), who analyze the transmission of macroeconomic shocks to bank risk taking (measured as the share of non-performing loans) and loan growth for the US, using disaggregated information for a large panel of US commercial banks within a FAVAR model. They notably point to heterogenous responses to expansionary monetary and house price shocks, as small banks extend more loans and more capitalized banks tend to make more risky investments (as can be gauged, with the benefit of hindsight, by looking at the change in bad loans over a horizon of one year). However, it is fair to note that they consider a much more heterogenous population of some 1500 commercial banks with assets larger than $25 million, whereas we focus on a contained sample of some 100 large bank holding companies with assets larger than \$3 billion, so that the potential for heterogenous behaviour at the bank level is a priori less in our case. Nevertheless, in order to check that our estimated macro shock to bank capital ratio is immune from the possible consequences of such heterogeneity, we restimated equation (5) on different sub-samples of banks, taking into account only the 25 or 50 largest institutions. As regression coefficients (not shown here for brevity) are not really affected (also less precisely estimated), we find confirmation of the homogeneity assumption. Importantly for our purpose, Figure 3 shows that the estimated aggregate capital ratio shock series also remains broadly unchanged when we restrict the sample to a smaller number of institutions.

Giving an economic interpretation to the sign of our aggregate shock series is not straightforward. Indeed, following a positive shock, a bank can increase its capital ratio by only increasing its capital, only decreasing its assets, increasing its capital more than it inflates its assets or decreasing its assets by more than its capital shrinks. In other words de-leveraging may be associated with either an expansion or a reduction in a bank's balance sheet. Mutatis mutandis, the same applies for a negative shock to bank capital ratios. To guide intuition, it may help to look at correlations between asset growth, equity growth and changes in the capital ratios at the individual level. Table 4 shows how the sign of shocks to the ratio relates to the sign of changes in its numerator (equity) and denominator (assets) at bank level within our sample. Note that roughly half of the capital ratio shocks in our sample are positive, which is consistent with the assumption that $E(\varepsilon_{i,t}) = 0$ in the panel regression. Looking at positive (i.e. deleveraging) shocks, most if not all of them (94%) are associated with stable or increasing equity, while about half of them are associated with increasing assets. In contrast, some 86% of negative ratio (i.e. leveraging) shocks tend to go in synch with increasing assets, while the equity base goes up in only two thirds of cases. From this we may guess that *negative* ratio shocks should have rather expansionary effects on the economy. The sign of the aggregate consequences of *positive* ratio shocks remains, however, unsettled at this stage and should be expected to depend on the size distribution of shocked banks at each point in time.

5.4 Validating the factor structure of macro series

In practice, having obtained series of realizations of the three real and nominal macro shocks stacked in η_t, as well as of the bank capital ratio shock ε_t, we get estimates of the parameters in equation (6) by using simple OLS regressions. Since it appears that usual information criteria are not very conclusive about the optimal number of lags to include in each polynomial, we try to keep the model as parsimonious as possible, while allowing for a sufficiently rich dynamic of the response of individual variables to the aggregate capital ratio shock. We thus choose one lag for the lagged dependent variable, one lag for the non-banking macro shocks and four lags for the capital ratio shock as our baseline specification. We nevertheless checked that allowing for a richer lag structure (up to four lags for each polynomial) does not qualitatively affect our conclusions. A comparison of IRFs for different sets of lags of the polyomials in equation (6) is presented in Figures 6-7. The figures confirm that our main results are quite robust to reasonable changes to lag selection.

An important underlying assumption of our approach is that the series in X have a factor structure and that the dynamic factors extracted from X also span the ancillary variables in Y. To check this, we conduct Wald tests of joint significance of the coefficients in the FADL regressions of individual macro series, as well as tests of the joint significance of the parameters associated with the contemporaneous and lagged bank capital ratio shock only. Table 5 presents the results, together with the share of the variance of each macro series that is explained by all regressors vs the capital ratio shock alone. The tests first confirm that our shock series indeed span all the real and nominal macro series stacked in X as well as most of the banking indicators in Y, with the exception of the growth of real estate loans. Interestingly, the null that capital ratio shocks do not matter for explaining macro series is rejected (at the 10% level) for several key activity variables, notably GDP, investment, industrial production, the consumption of non-durables and housing starts, as well as for the corporate spread. The aggregate capital ratio shock also turns out to be a significant determinant of most credit and banking indicators, with the exception of the growth of deposits and of real estate loans, as well as interest rates on personal and new car loans. It is important to note that this finding is not as such inconsistent with the fact that the capital ratio shock is by construction orthogonal to the contemporaneous common macro shocks driving X_t. Indeed, the capital ratio shock may first drive the idiosyncratic component of some of the macro series $X_{i,t}$ (the u_t term in equation 1). Besides, lags of the capital ratio shock may not be orthogonal with the common shocks in η_t. Finally, note that the factor structure also explains a large share of the variance of some key banking indicators, above 80% for the growth of C&I loans and bank credit rates, although these indicators were not part of the training sample used to extract the non-banking macro shocks.

Overall, the results presented in Table 5 suggest that it indeed makes sense to look at the IRFs of key macroeconomic and credit indicators to the aggregate capital ratio shock.

6 Assessing the macroeconomic effects of shocks to the leverage of large banks

Figure 4 presents the response of a selection of macro variables of interest in X_t to a positive bank capital ratio shock of one standard deviation (i.e. about 0.2 percentage points), together with bootstrapped confidence intervals at the 70% level.[20] First, we find a large and significant contractionary effect on GDP of this unexpected reduction in the leverage of large banks, with the components of aggregate demand that are a priori most sensitive to the availability of credit showing the largest reaction on impact. Indeed, total productive investment decreases by some 2 percentage points on impact, and slightly more in the second quarter after the shock. Similarly, consumption of durables drops immediately by some 1.5 percentage points, but the effect is short-lived and vanishes after one quarter. Also, consumption of non-durables and total consumption contract with a lag during a couple of quarters after the shock. The responses obtained for interest rates show that, while monetary policy does not seem to react to the bank capital ratio shock itself, the central bank will lower the short term rate by some 50 basis points two quarters after the shock to counteract its recessionary consequences. This persistent decrease in the policy rate is in turn reflected in lower risk-free interest rates along the whole yield curve. Finally, a deleveraging shock to bank capital ratios leads to an immediate (although short-lived) increase in the Baa corporate spread. Interestingly, this result echoes the evidence presented by Gilchrist and Zakrajsek (2012) regarding the link between their measure of the excess corporate bond premium - the premium required by corporate bond investors beyond the compensation for the measured default risk of firms - and the capacity of major financial institutions to take risk on their balance sheet, depending in turn on their capital structure. They notably find that a deterioration in the profitability of broker-dealers leads to rise in their CDS spreads, a good measure of the perceived default risk of these financial intermediaries, and an associated rise in the excess corporate bond premium, reflecting their reluctance to take on additional risk. As Gilchrist and Zakrajsek also provide evidence that this premium embedded in corporate spreads, and to some extent the total corporate spread itself, are good predictors of future economic activity, this suggests that the consequences of bank leverage

[20] Note that the response functions are presented in levels for the sake of clarity, which means that they show the cumulated effects of the capital ratio shock on the growth rates or changes of individual variables whenever the series are non-stationary (like e.g. GDP).

shocks for the excess corporate bond premium could provide a channel for the transmission of these shocks to activity, beyond the direct effect on lending.

Figure 5 in turn presents the responses of the credit and banking indicators stacked in Y, which we do not take into account when extracting the real and nominal shock series from the general macro dataset. Note that, again, none of these IRFs are constrained. Most interestingly, we find a large, significant, immediate and persistent decrease in most measures of aggregate credit considered, with the weakest response for consumer credit. Credit to firms (C&I loans and loans & leases) contracts more than credit to households for housing purposes, by some 2.5% on impact and 10% over the first year. Overall, a positive shock to bank capital ratios (i.e. a negative aggregate bank leverage shock) triggers a large and persistent fall in total bank credit and total bank assets over at least six quarters. Total commercial bank credit drops by 2% on impact and about 6% over the following year, the magnitude being similar for bank assets. Last but not least, we find that the deleveraging shock implies a significant rise in the spreads between some bank credit rates and monetary policy rates. The increase is notably large and persistent for interest rates on small loans to firms. The combination of decreasing loan volumes and increasing loan rates suggests that our estimated bank capital ratio shock does identify properly a negative credit supply shock. This is all the more noteworthy that we do not need to impose any sign restrictions to identify this shock.

The last two panels at the bottom of Figure 5 show the reaction of two other indicators used in related studies: the index of tightening of credit conditions according to the Loan Officer Survey, and the aggregate measure of the leverage of all US commercial banks as computed in the Flow of funds.[21] Credit standards do not seem to tighten following a positive shock to bank capital ratios, which suggests that, at least over our sample period, credit standards were not primarily tightened because of capital constraints on the side of banks.[22] This tends to be confirmed by the almost zero correlation we observe between our capital ratio shock and the aggreate bank lending standard shock provided by Basset et al.

[21] Due to a shorter available time series, the IRF for these last two variables are estimated over the period from 1992 to 2010.

[22] This may hold in aggregate, although some banks may indeed have tigntened standards and cut lending as a consequence of scarce capital, and in particular most recently in anticipation of more stringent Basel 3 capital requirements. In a recent paper, Basset and Covas (2012) use banks' own assessments of their capital adequacy as reported to the Fed's Survey on lending standards to study the link between capital adequacy and lending over the period 1996-2010.They find reduced loan growth at banks that tighten lending standards as a result of concerns about their current or future capital position relative to banks that do not report being capital constrained.

(2011).[23] Finally, we check that a positive capitalization shock according to our measure is indeed associated with a rise in the aggregate measure of US commercial bank leverage as taken from the FRED database.

As is apparent from the time series of the estimated aggregate bank capital ratio shocks in Figure 2, the amplitude of the capital ratio shocks during the climax of the recent financial crisis was quite unprecedented. This raises the question as to whether the obtained impulse responses only reflect the state of correlations during the crisis, or whether at least the sign of the responses is robust to the exclusion of the crisis episode. To check this, we re-run all regressions of macro variables on the estimated shocks on a sub-period ending in the second quarter of 2008, that is before the failure of Lehman and the intensification of the turmoil. Figures 8 and 9 present the estimated impulse responses for general macro variables and credit and banking variables respectively. Although the size of the responses is smaller, which is partly due to the fact that the standard deviation of the capital ratio shock is smaller over the pre-crisis period, the sign and shape of the responses are largely unchanged, which confirms the robustness of our baseline results.

All the results presented above are based on the implicit assumption that positive and negative shocks to bank capital ratios have symmetric effects on aggregate credit and economic activity. However, this is far from certain, since an unexpected increase in capital ratios (a reduction in leverage) may reflect a binding capital constraint, be it regulatory or imposed by market discipline, while an unexpected decrease in capital ratios (a surge in leverage) may not. To investigate possible asymmetric effects of bank leverage shocks, we thus run the same regressions of all the macro variables on their lags and our estimates of macro and bank capital shocks, but we replace the $\widehat{\varepsilon}_t$ series with both its positive and negative parts -i.e. $\max(\widehat{\varepsilon}_t, 0)$ and $\min(\widehat{\varepsilon}_t, 0)$. Figures 10 and 13 respectively present the asymmetric responses of general macro variables and credit and banking indicators to the positive and the negative shocks.

Interestingly, we find a strongly asymmetric effect of positive capital ratio shocks, as opposed to negative ones, on real activity and credit. While real activity and aggregate bank credit still contract on impact after an asymmetric deleveraging shock, the size of this contraction is larger than it was before under the assumption of a symmetric response to the capital ratio shock. For instance, the immediate response of GDP and productive

[23] As we do here, BCDZ proceed in two steps, taking advantage of detailed information available at the bank level. They first construct exogenous shocks to banks' individual responses to the SLOOS, using a panel regression of individual tightening indexes on bank-specific and macro indicators, and then aggregate these individual innovations as a weighted average.

investment is about twice as large, while the response of C&I loans is about 1.5 times larger after one year. Moreover, the average interest rate on C&I loans increases on impact by some two percentage points and remains higher for almost a year. In contrast, we find no significant response of either GDP or investment over the first few quarters after an asymmetric shock *increasing* bank leverage. On the credit side however, we note a short-lived increase in credit to firms, total bank credit and bank assets overall. Finally, loan rates slighlty decrease on impact or do not react significantly.

Finally, we compare our results with the results we obtain in the FADL framework using the measure of the aggregate-capital-to assets ratio shock for US commercial banks estimated by Berrospide and Edge (2010), henceforth BE. In their paper, they estimate a small monetary VAR with six variables: real GDP growth, core GDP price inflation, the federal funds rate, the growth in total loans granted by commercial banks and savings and thrift institutions in the US, the aggregate capital-to-assets ratio of US commercial banks taken from the Federal Reserve's FRED database, and, last, the lending standard indicator provided by the SLOOS (in that order). In a very standard way, they then extract an aggregate series of shocks to the capital ratio variable by assuming short term restrictions consistent with a Cholesky orthogonalization of the covariance matrix of estimated VAR residuals. We replicate their procedure here and plot the estimated aggregate capital ratio shock (hence BE shock) in Figure 14 against our own measure. Due to the limited availability of some of the data used, the series starts in 1990 Q4 only. The BE series has a much larger standard deviation than our estimate, close to one percentage point. This higher volatility of the BE shock series may reflect a combination of factors. First, the aggregate capital ratio measure provided by the Federal Reserve relates to all commercial banks in the US, instead of the biggest BHCs. It may thus be affected by the behaviour of smaller or specialized institutions. Furthermore, the commercial bank level, as opposed to the consolidated one, may not be the relevant one for setting the capital ratio target of banks belonging to larger groups. Nevertheless, the BE shock series is positively correlated to ours (with a correlation of 0.46). In particular, both measures identify large negative capital ratio shocks in 1994 and 2008, and peaks in 2004 and early 2009, as the US Treasury started injecting fresh capital into some banks and the Fed launched the Supervisory Capital Assessment Program requiring large banks to speed up their capital building. For comparison purposes, we then run once more the FADL regressions as in equation 6, while replacing our measure of the aggregate capital-to-assets ratio shock by the BE shock.

Figures 15 and 16 show the responses of the same macro and credit variables to both bank capital ratio shocks, the BE one and ours (denoted MS below for convenience). Both shocks have been standardized, so that the sizes of the responses can be compared. Note also that panels 8, 14 and 15 of Figure 16 present the reactions of the same aggregate banking indicators as in BE, so that the responses to the BE shock plotted here are directly comparable with the responses shown in their paper.[24]

Contrary to BE, we first find that loans by commercial banks and thrift institutions and lending standards do not react much to a positive BE capital ratio shock, total loans increasing slowly only after one year. Since the short term responses need not be restricted in our set-up, we however find a negative response of output growth on impact to their shock, while in their paper they only observe a significant decline in GDP growth two years after the shock. Interestingly, we can also obtain the responses of all the macro variables in our rich dataset to their estimated capital ratio shock. In particular, looking at credit aggregates, we find that the contractionary response of total commercial bank credit as well as most of its components (with the exception of consumer loans) is rather subdued after a positive BE shock. This however contrasts with their finding of a surge in the specific credit aggregate included in their VAR, suggesting that the latter response may be spurious, probably due to a misspecification of their small-scale VAR or an inadequate identification scheme. Last but not least, we also find that bank loan rates do not react or decrease on impact following a BE deleveraging shock, which suggests that they did not identify a credit supply shock. Finally, the response of GDP to the MS shock is both larger and more pesistent than in the BE case. Both findings point to significant benefits of both extracting the capital ratio shock from a microeconomic database and working within a data-rich macroeconomic framework as we do here.

7 Conclusion

In this paper, we have studied the macroeconomic consequences of a shock to the capital-to-asset ratio of large US bank holding companies. An important feature of our work is that we consider a rich database of both bank balance sheet information and macroeconomic aggregates, thus bridging the usual gap in the literature between micro and macro assessments of the consequences of bank capital ratio fluctuations for lending and growth, and overcoming some of the standard endogeneity issues.

We have found robust evidence that our measure of leverage shocks to the large US banks

[24] Note however that they present IRFs of standardized variables (growth rates) while we show cumulated IRFs for stationnarized variables.

matters for understanding fluctuations in credit aggregates as well as the US business cycle. Our framework is flexible enough to allow us to compute the responses of the macroeconomic variables in our database to any exogenous series of shocks constructed in other papers. Then, comparing the responses of activity and credit aggregates to our capital ratio shock with the responses obtained when using a capital ratio shock extracted using a small macro VAR and recursive ordering (as in Berrospide and Edge, 2010), we notably obtain larger and more persistent impacts. Besides, bank lending contracts and lending rates rise after a deleveraging shock as we measure it, suggesting that we have identified a negative credit supply shock. This comparison illustrates the benefits of both extracting the capital ratio shock from a microeconomic database and of working within a data-rich macroeconomic framework, as we do here.

Although we feel the evidence presented here can be a useful contribution to the policy debate about the pros and cons of the heightened capital requirements being imposed on large banking corporations, we see our results as providing at best an upper bound of the likely short-run adverse economic impact of a surprise increase in capital requirements. Indeed, as said earlier, our capital ratio shocks at the individual level, however convincingly orthogonalized to possible credit demand effects, remain a combination of various unobservable influences affecting bank leverage. Tighter regulations, if any, are only one possible source of the volatility of the innovations to capital ratios we can observe in our sample. That said, our results lend support to the view that a switch to tighter capital regulations should be gradual and operate preferably through accumulated earnings in order to minimize its short-run negative consequences for the economy (see e.g. Kashyap, Stein and Hanson, 2010).

A Data

A.1 Definition and sources of bank variables

Variable name	FR Y-9C code or details of variable definition
Total assets	BHCK2170
Equity	BHCK3210
Net income	BHCK4340
Net chargeoffs	BHCK4635 - BHCK4605
Real estate loans	BHCK1410
C&I loans	BHCK1763 + BHCK1764
Capital to assets ratio	Equity / Total assets * 100
Return on assets	Net income / Quarterly average of Total assets * 400
Net chargeoffs to assets ratio	Net chargeoffs / Quarterly average of Total assets * 400
Size	log(Total assets)

A.2 List of banks included in the panel

Note: Assets are expressed $ thousand.

No.	RSSID	Name	Min. assets	Max. assets	# Obs.	Time span	
						Start	End
1	1951350	CITIGROUP INC.	6,69E+08	2,36E+09	46	1998q4	2010q1
2	1073757	BANK OF AMERICA CORPORATION	2,39E+07	2,34E+09	96	1986q2	2010q1
3	1039502	JPMORGAN CHASE & CO.	5,60E+07	2,25E+09	96	1986q2	2010q1
4	1120754	WELLS FARGO & COMPANY	1,96E+07	1,31E+09	96	1986q2	2010q1
5	1042351	CITICORP	1,83E+08	9,71E+08	77	1986q2	2005q2
6	1073551	WACHOVIA CORPORATION	1,94E+07	8,12E+08	90	1986q2	2008q3
7	2816906	TAUNUS CORPORATION	1,71E+08	7,60E+08	44	1999q2	2010q1
8	2945824	METLIFE. INC.	2,52E+08	5,66E+08	37	2001q1	2010q1
9	1068294	BANK ONE CORPORATION	1,12E+07	3,27E+08	73	1986q2	2004q2
10	1037115	J.P. MORGAN & CO. INCORPORATED	7,27E+07	2,99E+08	58	1986q2	2000q3
11	1069778	PNC FINANCIAL SERVICES GROUP. INC.. THE	2,02E+07	2,91E+08	96	1986q2	2010q1
12	1111435	STATE STREET CORPORATION	6172269	2,87E+08	96	1986q2	2010q1
13	1119794	U.S. BANCORP	1,70E+07	2,82E+08	96	1986q2	2010q1
14	1026016	BANKAMERICA CORPORATION	9,28E+07	2,65E+08	49	1986q2	1998q2
15	1113514	FLEETBOSTON FINANCIAL CORPORATION	1,00E+07	2,12E+08	72	1986q2	2004q1
16	1131787	SUNTRUST BANKS. INC.	1,88E+07	1,89E+08	96	1986q2	2010q1
17	1069125	NATIONAL CITY CORPORATION	1,25E+07	1,55E+08	90	1986q2	2008q3
18	1033470	BANK OF NEW YORK COMPANY. INC.. THE	1,84E+07	1,26E+08	85	1986q2	2007q2
19	1199778	FIRST CHICAGO NBD CORPORATION	1,86E+07	1,22E+08	50	1986q2	1998q3
20	1040795	CHASE MANHATTAN CORPORATION	9,00E+07	1,21E+08	39	1986q2	1995q4
21	1070345	FIFTH THIRD BANCORP	3142089	1,20E+08	96	1986q2	2010q1
22	1027095	WELLS FARGO & COMPANY	4,27E+07	1,09E+08	50	1986q2	1998q3
23	1068025	KEYCORP	8633737	1,05E+08	96	1986q2	2010q1
24	1245415	HARRIS FINANCIAL CORP.	9880000	8,83E+07	96	1986q2	2010q1
25	1378434	UNIONBANCAL CORPORATION	4091351	8,56E+07	96	1986q2	2010q1
26	1199611	NORTHERN TRUST CORPORATION	7674379	8,21E+07	96	1986q2	2010q1
27	1025608	BANCWEST CORPORATION	3346544	7,99E+07	96	1986q2	2010q1
28	1112076	BANKBOSTON CORPORATION	3,04E+07	7,76E+07	54	1986q2	1999q3
29	1201028	FIRST CHICAGO CORPORATION	3,91E+07	7,57E+07	38	1986q2	1995q3
30	1136157	WACHOVIA CORPORATION	1,75E+07	7,56E+07	61	1986q2	2001q2
31	1020340	HARRIS BANKCORP. INC.	1,16E+07	6,82E+07	82	1989q4	2010q1
32	1199844	COMERICA INCORPORATED	9285234	6,79E+07	96	1986q2	2010q1
33	1078529	BBVA USA BANCSHARES. INC.	3494388	6,78E+07	96	1986q2	2010q1
34	1871159	MBNA CORPORATION	5146165	6,30E+07	60	1991q1	2005q4
35	1416774	NATIONSBANK TEXAS BANCORPORATION. INC.	3,04E+07	6,24E+07	33	1990q1	1998q1
36	1199497	M&I LLC	4866038	6,08E+07	86	1986q2	2007q3
37	1021075	REPUBLIC NEW YORK CORPORATION	1,68E+07	5,99E+07	54	1986q2	1999q3
38	1023538	FIRST INTERSTATE BANCORP	4,89E+07	5,91E+07	40	1986q2	1996q1
39	1068191	HUNTINGTON BANCSHARES INCORPORATED	7016598	5,60E+07	96	1986q2	2010q1
40	1078604	AMSOUTH BANCORPORATION	5264186	5,43E+07	82	1986q2	2006q3
41	1079441	SOUTHTRUST CORPORATION	4571219	5,39E+07	74	1986q2	2004q3
42	1068762	MELLON FINANCIAL CORPORATION	2,87E+07	5,10E+07	84	2013q2	2033q4
43	1078332	REGIONS FINANCIAL CORPORATION	3844149	4,99E+07	73	1986q2	2004q2
44	1116300	CORESTATES FINANCIAL CORP	1,21E+07	4,85E+07	48	1986q2	1998q1
45	1076776	BARNETT BANKS. INC.	1,62E+07	4,65E+07	47	1986q2	1997q4
46	1093586	BOATMEN'S BANCSHARES. INC.	8890520	4,12E+07	43	1986q2	1996q4
47	1094640	FIRST HORIZON NATIONAL CORPORATION	5234059	4,01E+07	96	1986q2	2010q1
48	1033872	SUMMIT BANCORP.	5555961	3,97E+07	59	1986q2	2000q4

49	1199479	FIRSTAR HOLDINGS CORPORATION	6443605	3,87E+07	54	1986q2	1999q3
50	1248612	FIRST FIDELITY BANCORPORATION	2,82E+07	3,62E+07	32	1988q1	1995q4
51	1094211	MERCANTILE BANCORPORATION INC.	6287766	3,60E+07	53	1986q2	1999q2
52	1427471	FLEET NEW YORK. INC.	1,21E+07	3,54E+07	32	1989q4	1997q3
53	2467175	UNION PLANTERS HOLDING CORPORATION	7262128	3,50E+07	32	1996q4	2004q3
54	1025701	U.S. BANCORP	8411418	3,40E+07	45	1986q2	1997q2
55	1021758	NATWEST HOLDINGS INC.	1,09E+07	3,37E+07	40	1986q2	1996q1
56	1033993	FIRST FIDELITY INCORPORATED	1,40E+07	3,35E+07	39	2016q2	2025q3
57	1020603	CONTINENTAL BANK CORPORATION	2,16E+07	3,34E+07	33	1986q2	1994q2
58	1035166	NATIONAL WESTMINSTER BANCORP NJ	3679044	3,20E+07	32	2016q2	2023q4
59	1473562	BANC ONE TEXAS CORPORATION	1,28E+07	3,13E+07	43	1990q1	2000q3
60	1022362	LASALLE NATIONAL CORPORATION	3431221	2,90E+07	38	1989q4	1999q1
61	1023314	CITICORP HOLDINGS. INC.	1,54E+07	2,89E+07	39	1990q1	1999q3
62	1023453	SUNTRUST BANKS OF GEORGIA. INC.	9459810	2,89E+07	40	1990q1	1999q4
63	1250932	BANC ONE OHIO CORPORATION	1,50E+07	2,83E+07	32	1990q1	1997q4
64	1072237	CRESTAR FINANCIAL CORPORATION	8418294	2,78E+07	55	1986q2	1999q4
65	2081124	GREENPOINT FINANCIAL CORP.	6955179	2,70E+07	43	1994q1	2004q3
66	1199648	FIRST OF AMERICA BANK CORPORATION	5461940	2,46E+07	47	1986q2	1997q4
67	1199705	OLD KENT FINANCIAL CORPORATION	4507645	2,45E+07	60	1986q2	2001q1
68	1140743	MIDLANTIC CORPORATION	1,33E+07	2,43E+07	36	1986q4	1995q3
69	1024058	FIRST SECURITY CORPORATION	4887095	2,33E+07	69	1986q2	2003q2
70	1078921	HIBERNIA CORPORATION	3051117	2,32E+07	78	1986q2	2005q3
71	1078426	FIRST AMERICAN CORPORATION	4968735	2,22E+07	54	1986q2	1999q3
72	2744894	FIRST BANCORP	4017352	2,06E+07	46	1998q4	2010q1
73	1072291	FIRST UNION CORPORATION OF VIRGINIA	5309175	2,03E+07	45	1986q2	1997q2
74	1074660	ALLFIRST FINANCIAL INC.	4768073	1,89E+07	68	1986q2	2003q1
75	2389941	TCF FINANCIAL CORPORATION	7429623	1,82E+07	52	1997q2	2010q1
76	1049341	COMMERCE BANCSHARES. INC.	4917787	1,81E+07	96	1986q2	2010q1
77	2801546	W HOLDING COMPANY. INC.	3374588	1,81E+07	42	1999q4	2010q1
78	1070251	STAR BANC CORPORATION	3688217	1,73E+07	50	1986q2	1998q3
79	1102367	CULLEN/FROST BANKERS. INC.	3042869	1,68E+07	96	1986q2	2010q1
80	1028739	BANC ONE ARIZONA CORPORATION	1,01E+07	1,58E+07	47	1986q2	1997q4
81	1023060	MERIDIAN BANCORP. INC.	6313644	1,52E+07	40	1986q2	1996q1
82	1025309	BANK OF HAWAII CORPORATION	4653763	1,50E+07	96	1986q2	2010q1
83	1072107	SIGNET BANKING CORPORATION	8522229	1,30E+07	46	1986q2	1997q3
84	1888193	WILMINGTON TRUST CORPORATION	3969244	1,26E+07	75	1991q3	2010q1
85	1246702	PEOPLE'S MUTUAL HOLDINGS	5482306	1,23E+07	72	1988q3	2006q2
86	1199714	MICHIGAN NATIONAL CORPORATION	7812468	1,20E+07	60	1986q2	2001q1
87	1071968	FIRST VIRGINIA BANKS. INC.	3602841	1,13E+07	69	1986q2	2003q2
88	1074875	CENTRAL FIDELITY BANKS. INC.	3634415	1,08E+07	46	1986q2	1997q3
89	1246216	FRANKLIN RESOURCES. INC.	5900311	9942115	36	2001q2	2010q1
90	2894230	DISCOUNT BANCORP. INC.	4610604	9519594	41	2000q1	2010q1
91	1080371	LOUISIANA BANC ONE CORPORATION	3421048	9507297	50	1986q2	1998q3
92	1200432	BANC ONE INDIANA CORPORATION	4284241	9400736	38	2016q2	2025q2
93	2847115	SANTANDER BANCORP	6571193	9288663	40	2000q2	2010q1
94	1028953	WEST ONE BANCORP	3264714	9244503	38	1986q2	1995q3
95	1080148	SUNTRUST BANKS OF TENNESSEE. INC.	4962702	9114637	42	2016q2	2026q2
96	3005332	F.N.B. CORPORATION	4062977	8799534	36	2001q2	2010q1
97	1199488	BANC ONE WISCONSIN CORPORATION	3846284	8755366	35	2016q2	2024q3
98	2477754	INVESTORS BANCORP. MHC	3172821	8738437	53	1997q1	2010q1
99	1079638	BANK SOUTH CORPORATION	3024519	7684650	39	1986q2	1995q4
100	1075126	RIGGS NATIONAL CORPORATION	4426221	7637650	76	1986q2	2005q1
101	1072554	SOUTH CAROLINA NATIONAL CORPORATION	4265638	7424140	38	1986q2	1995q3
102	2947435	BBVA PR HOLDING CORPORATION	4724153	7045588	38	2000q4	2010q1
103	1034888	CHEMICAL NEW JERSEY HOLDINGS. INC.	3167695	6217134	34	2016q2	2024q2
104	1130892	PREMIER BANCORP. INCORPORATED	3760037	5511975	38	1986q2	1995q3

A.3 Macroeconomic time series used in the factor analysis

The transformation codes are: 1 = no transformation; 2 = first difference; 4 = logarithm; 5 = first difference of logarithm; 0 = variable not used in the estimation (only used for transforming other variables).

No.	Series Code	T-Code	Series Description
			Activity and labour market
1	CUMFN	2	Capacity Utilization: Manufacturing (NAICS)
2	GDPC1	5	Real Gross Domestic Product, 1 Decimal
3	GPDI	5	Gross Private Domestic Investment
4	INDPRO	5	Industrial Production Index
5	NAPM	2	ISM Manufacturing: PMI Composite Index
6	PAYEMS	5	Total Nonfarm Payrolls: All Employees
7	RPCE	5	Real PCE : Personal consumption expenditures (PCE)
8	RPCE-DUR	5	Real PCE Durable goods
9	RPCE-NONDUR	5	Real PCE Nondurable goods
10	UNRATE	1	Civilian Unemployment Rate
11	USCOINALG	5	US COMPOSITE INDEX - 4 COINCIDENT INDICATORS
			Prices
12	CPIAUCSL	5	Consumer Price Index for All Urban Consumers: All Items
13	CPILFESL	5	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy
14	CRBSPOT	5	CRB Spot Index (commodity price index)
15	IR	5	Import (End Use): All commodities
16	OILPRICE	5	Spot Oil Price: West Texas Intermediate
17	PPIACO	5	Producer Price Index: All Commodities
18	PPIFGS	5	Producer Price Index: Finished Goods
			Housing
19	HOUST	4	Housing Starts: Total: New Privately Owned Housing Units Started
20	USCSHPE	5	US S&P/CASE-SHILLER NATIONAL HOME PRICE INDEX SADJ
			Interest rates and corporate spreads
21	AAA-spread	1	BOND YIELD: MOODY'S AAA CORPORATE (% PER ANNUM) - 10 y. Treas. yield
22	BAA-spread	1	BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM) - 10 y. Treas. yield
23	EFF-EXCHUS	5	EFF.EXCH.RATE, NOMINAL, USD AG. MAJOR CURRENCIES
24	FEDFUNDS	1	FEDFUNDS, Effective Federal Funds Rate
25	GS1	1	1-Year Treasury Constant Maturity Rate
26	GS10	1	10-Year Treasury Constant Maturity Rate
27	GS2	1	2-Year Treasury Constant Maturity Rate
28	GS3	1	3-Year Treasury Constant Maturity Rate
29	GS5	1	5-Year Treasury Constant Maturity Rate
30	RIFSGFSM06-N.M	1	6-month Treasury bill secondary market rate discount basis
31	S&PCOMP	5	S&P 500 COMPOSITE - PRICE INDEX
			Credit : Bank credit + subcomponents + lending standards
1	BK-CIL	5	Commercial and industrial loans, all commercial banks (Fed H8)
2	BK-CLK	5	Consumer loans, all commercial banks (Fed H8)
3	BK-CRED	5	Bank credit, all commercial banks (Fed H8)
4	BK-DEPO	5	Deposits, all commercial banks (Fed H8)
5	BK-LLEASES	5	Loans and leases in bank credit, all commercial banks (Fed H8)
6	BK-REL	5	Real estate loans, all commercial banks (Fed H8)
7	BK-TOTASS	5	Total assets, all commercial banks (Fed H8)
8	TOTLOANS-BK-SAV	5	Total loans commercial banks + savings institutions (Fed Z1)
9	SPREAD PERSONAL	1	Lending rates at commercial banks, 24 Months personal loans (SCC, Fed G19)
10	SPREAD CAR	1	Lendinf rates at commercial banks, 48 Months new car loans (SCC, Fed G19)
11	SPREAD CIL	1	C&I loans rates, all loans (STBL, Fed E2)
12	SPREAD CIL Large	1	C&I loans rates, more than $1 billion (STBL, Fed E2)
13	SPREAD CIL Small	1	C&I loans rates, less than $100 thousands (STBL, Fed E2)
14	DRTSCILM	1	Net Percent. of Domestic Respondents Tightening Standards for C&I loans to large firms
15	EQTA	1	Total Equity / Total Assets, all commercial banks (Source: FRED)

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	N	mean	sd	p25	p50	p75
Assets ($m)	6,137	76,365.25	216220.96	9,055.81	19,709.15	48,207.00
Capital-to-assets	6,137	8.05	5.13	6.49	7.54	8.67
ROA	6,137	2.64	3.33	1.22	2.42	3.79
ROE	6,137	27.53	213.23	16.29	31.92	49.29
Loans-to-assets	6,137	60.52	14.99	56.30	64.10	69.67
Mortgage loans-to-assets	6,137	26.46	12.76	18.67	26.46	33.70
C&I loans-to-assets	6,137	16.26	8.01	11.33	15.87	20.75
Net chargeoffs-to-assets	6,137	1.16	1.46	0.30	0.70	1.45

Table 1: Summary statistics for bank variables.

	N	mean	sd	p25	p50	p75
SP500 volatility	96	0.44	0.27	0.28	0.38	0.49
Exp. short rate change	96	0.34	0.48	0.02	0.29	0.63
Exp. GDP growth	96	2.64	0.63	2.32	2.67	3.01

Table 2: Summary statistics for macroeconomic expectations variables.

	(1)	(2)	(3)	(4)
Lagged capital ratio	0.9328***	0.9309***	0.9318***	0.9307***
	(98.48)	(96.08)	(95.67)	(94.72)
Size	0.0940***	0.1012***	0.0969***	0.0995***
	(3.73)	(4.02)	(3.82)	(3.95)
ROA	-0.0055	-0.0054	−0.0065*	-0.0059
	(-1.45)	(-1.43)	(-1.74)	(-1.60)
Net chargeoffs / assets	0.0255**	0.0242**	0.0260**	0.0244**
	(2.31)	(2.16)	(2.35)	(2.18)
Real estate loans / assets	-0.0016	-0.0021	-0.0018	-0.0020
	(-1.07)	(-1.32)	(-1.20)	(-1.29)
C&I loans / assets	−0.0051**	-0.0035	−0.0042*	-0.0036
	(-2.09)	(-1.43)	(-1.75)	(-1.46)
FHC status	0.0102	0.0126	0.0203	0.0200
	(0.21)	(0.25)	(0.41)	(0.39)
Merger dummy	0.1053**	0.1068**	0.1046**	0.1058**
	(2.52)	(2.57)	(2.51)	(2.54)
SP500 volatility		−0.0374**	-0.0302	−0.0387**
		(-2.04)	(-1.58)	(-2.14)
Exp. change policy rate		0.0680***		0.0545**
		(3.26)		(2.57)
Exp. change GDP growth		−0.0422**		-0.0331
		(-2.08)		(-1.64)
SWIPC1			0.0271**	0.0225*
			(2.26)	(1.86)
SWIPC2			0.0113	0.0092
			(1.56)	(1.27)
SWIPC3			0.0011	-0.0023
			(0.13)	(-0.26)
Observations	6026	6026	6026	6026
R^2	0.872	0.873	0.873	0.873

Table 3: Determinants of BHC capital-to-asset ratios. Note: The dependent variable is the capital to asset ratio of individual banks as in equation (2). The panel OLS regression is run with bank fixed effects. Robust t-stats are given in parentheses. *, **, *** denote significance at the 10, 5 and 1 percent levels respectively. SWIPC1 to SWIPC3 refer to the macro shocks extracted from the large dataset X of real and nominal macroeconomic non-banking variables using a factor model as explained in text. A constant and seasonal dummies are included but not reported.

			$\Delta(\text{Assets}_{i,t})$	
			< 0	> 0
$\varepsilon_{i,t} < 0$	$\Delta(\text{Equity}_{i,t})$	< 0	5.4	11.4
		≥ 0	1.8	31.9
$\varepsilon_{i,t} \geq 0$	$\Delta(\text{Equity}_{i,t})$	< 0	3.1	0.3
		≥ 0	21.1	25.2

Table 4: Breakdown of individual capital ratio shocks according to the sign of contemporaneous changes in bank equity and total assets (in percentage of total number of individual shocks).

	F-test p-value		R-squared	
ACTIVITY MEASURES	$\alpha(L)$	$\alpha_\varepsilon(L)$	Total	Marginal
Capital utilization	0.0000	0.0568	0.7991	0.0267
GDP	0.0000	0.0917	0.7024	0.0185
Investment	0.0000	0.0088	0.5992	0.0422
Industrial production	0.0000	0.0329	0.7835	0.0406
PMI	0.0000	0.1407	0.5068	0.0401
Consumption	0.0000	0.6062	0.6368	0.0117
Cons: durables	0.0000	0.3421	0.3975	0.0238
Cons: non-durables	0.0000	0.0716	0.5985	0.0284
Employment	0.0000	0.3970	0.8702	0.0072
CPI	0.0000	0.0156	0.7660	0.0308
Housing	0.0000	0.0361	0.9651	0.0043
House prices	0.0000	0.3250	0.6487	0.0536
FFR	0.0000	0.8441	0.9643	0.0006
T-Bill 10Y	0.0000	0.2398	0.9590	0.0012
B-spread	0.0000	0.0008	0.9276	0.0151
CREDIT MEASURES	$\alpha(L)$	$\alpha_\varepsilon(L)$	Total	Marginal
Commercial and industrial loans	0.0000	0.0595	0.8002	0.0267
Consumer loans	0.0014	0.0407	0.2616	0.0966
Bank credit	0.0000	0.0002	0.3646	0.1288
Deposits	0.0216	0.1429	0.2625	0.1039
Loans&Leases in bank credit	0.0000	0.0072	0.5140	0.1077
RE loans	0.2277	0.1274	0.2425	0.0643
Loans Banks + Thrift	0.0000	0.0004	0.4404	0.1263
Total loans	0.0000	0.0040	0.6856	0.0790
Spread Personal Loans	0.0002	0.2458	0.9310	0.0020
Spread Car Loans	0.0124	0.9282	0.9357	0.0006
Spread All CIL	0.0000	0.0014	0.8307	0.0328
Spread Large CIL	0.0000	0.0009	0.8196	0.0333
Spread Small CIL	0.0000	0.0684	0.8821	0.0120
Standard	0.0000	0.0382	0.8668	0.0136
Equity / Assets	0.0000	0.0000	0.5131	0.3183

Table 5: Testing the factor structure of individual macroeconomic series. Note: The F-test tests the null that the coefficients in the FADL regression of a given macro series are jointly zero (col. 1). In the second column, we test the null that only coefficients of the bank leverage shocks are jointly zero. P-values are obtained by bootstrap. Columns 3 and 4 display the share of variance explained by the FADL regressors and the marginal explanatory power of the current and lagged bank leverage shocks, respectively.

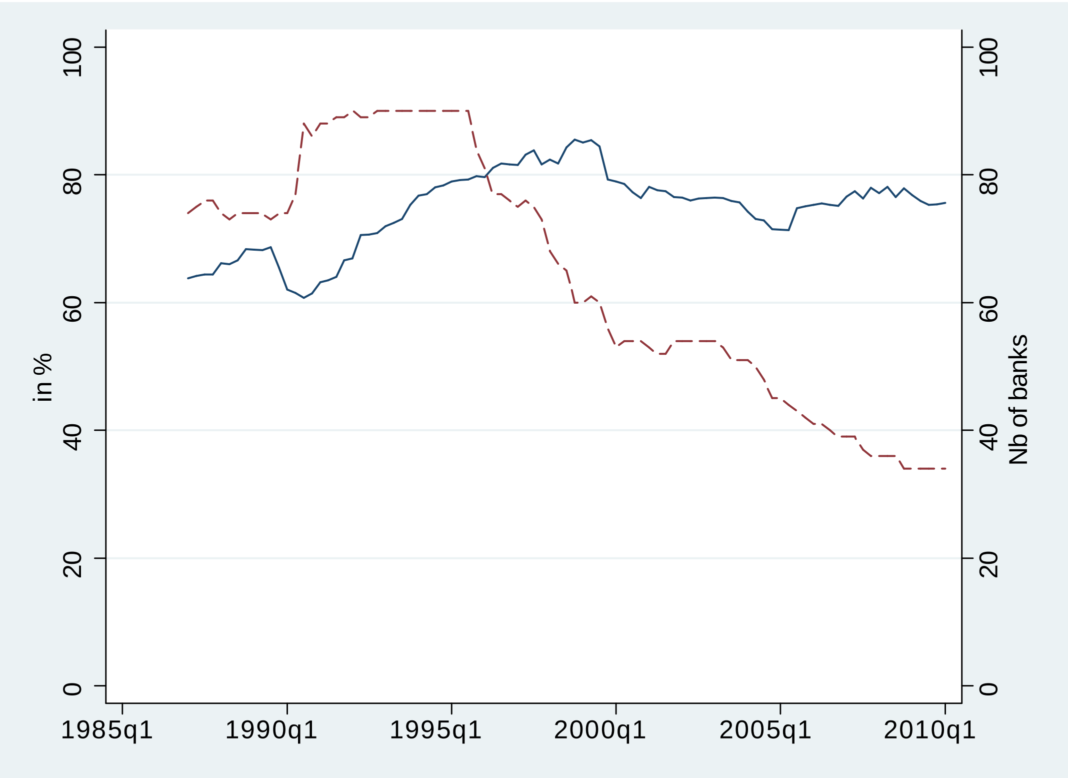

Figure 1: Share of banks in sample out of total US bank assets (solid line) and number of banks in panel through time (dashed line).

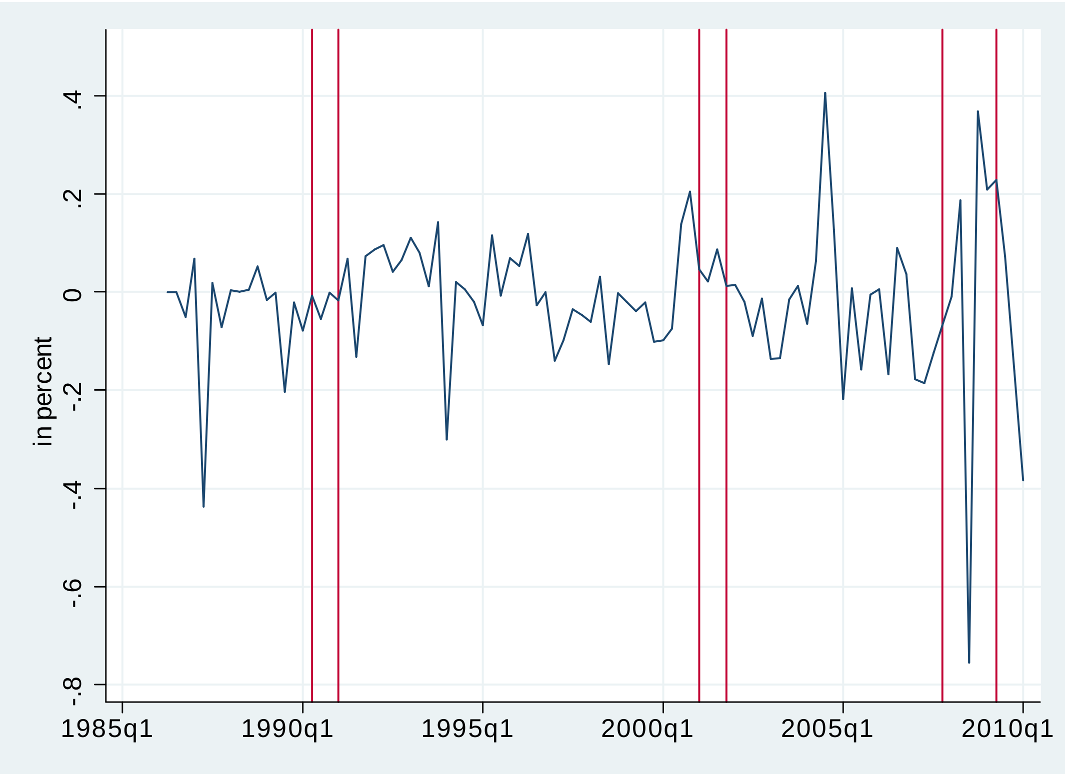

Figure 2: Estimated aggregate bank capital ratio shocks. Vertical lines delimit NBER recesssion dates.

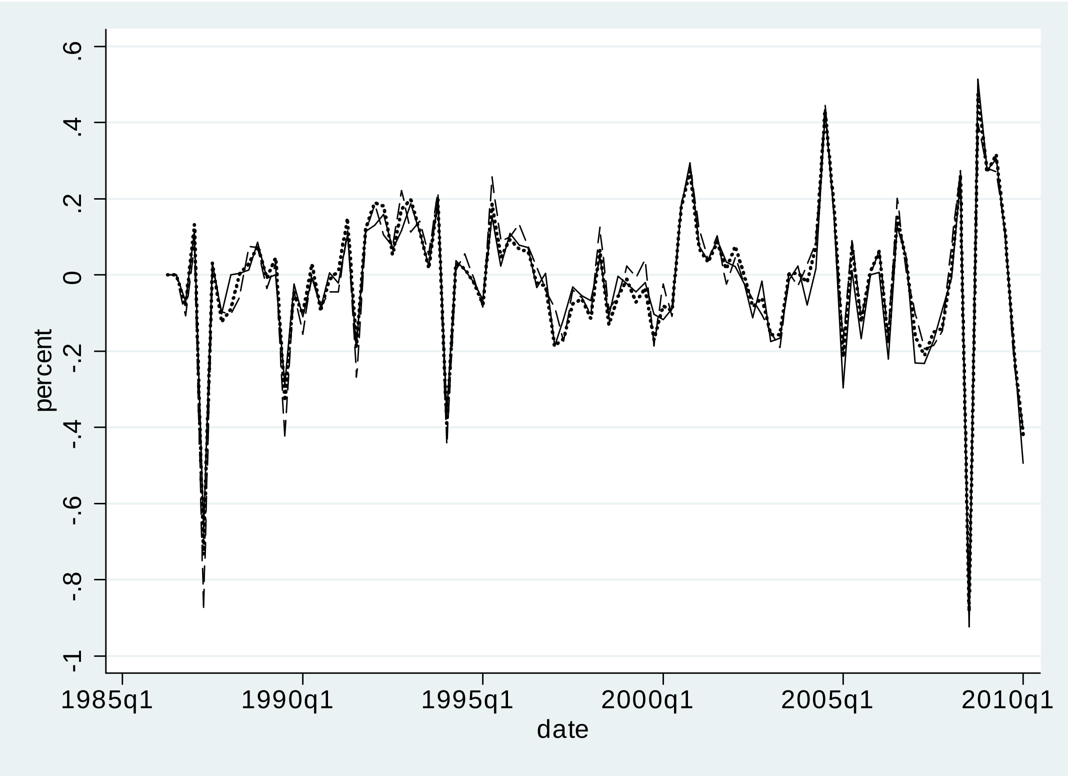

Figure 3: Estimated aggregate bank capital ratio shocks using various samples of BHCs: all the 104 banks in the baseline sample (solid), the 25 largest (dashed) and the 50 largest (dotted line).

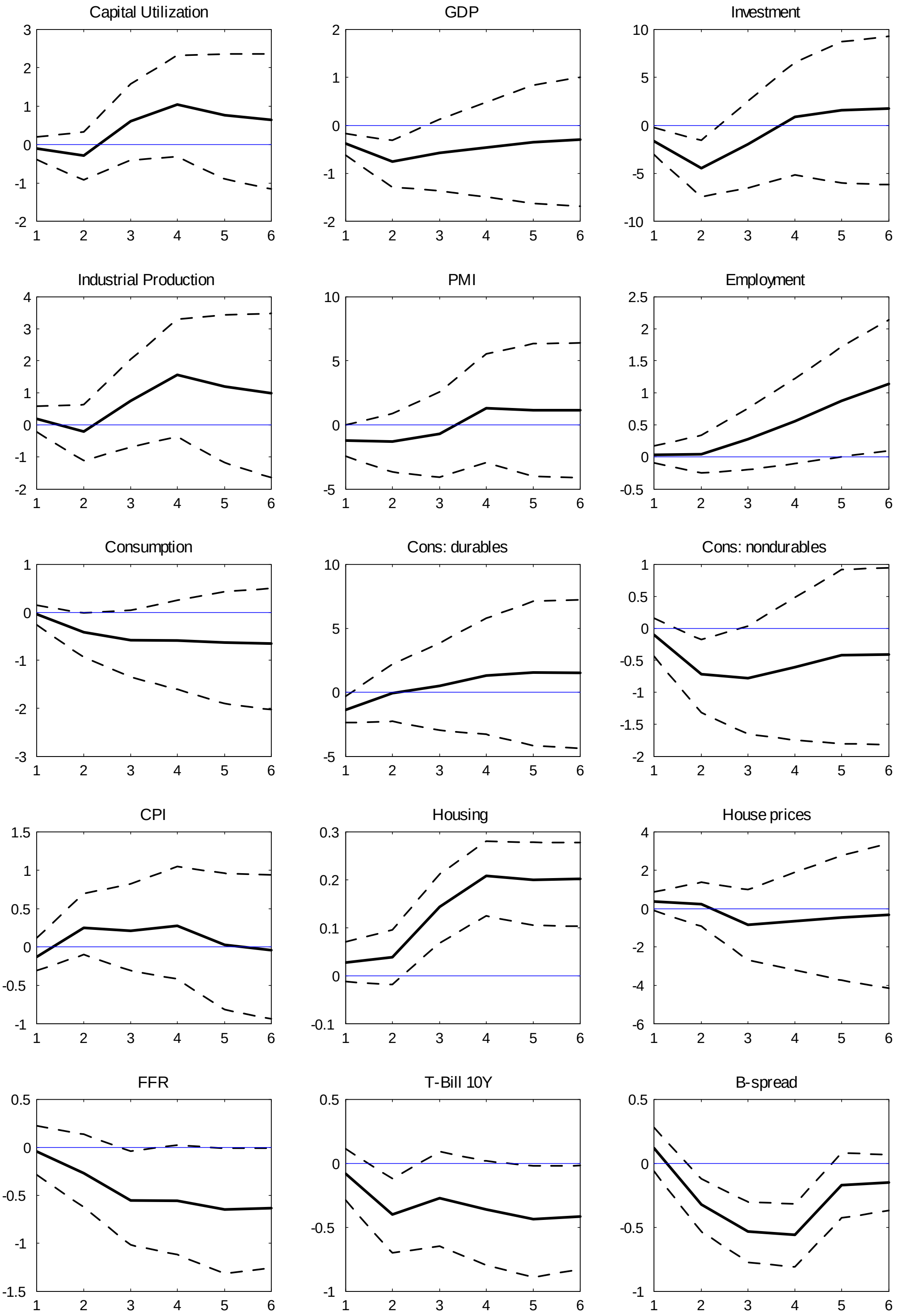

Figure 4: Impulse response functions of macroeconomic variables in X_t to a negative bank leverage shock (with 70 percent confidence intervals)

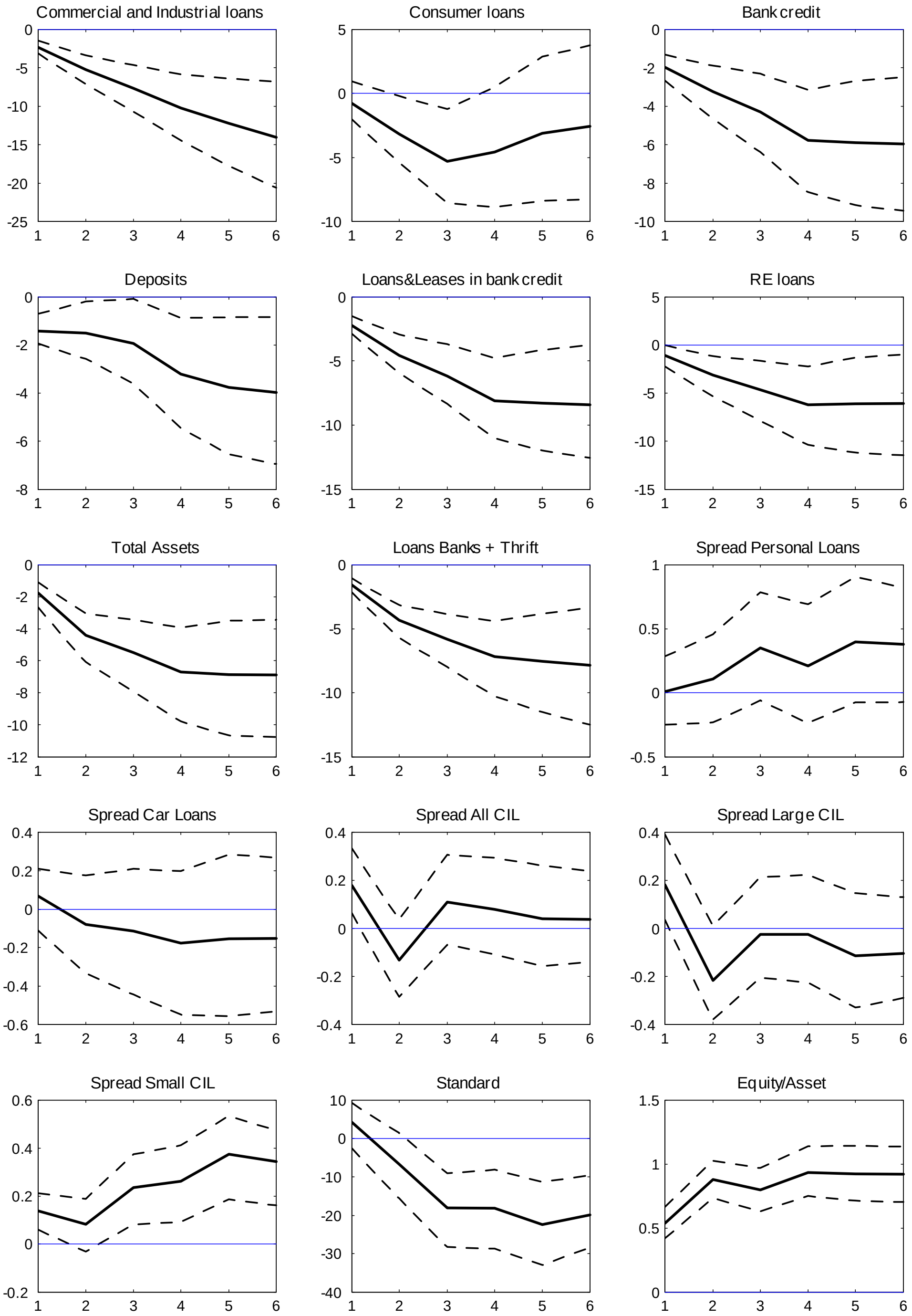

Figure 5: Impulse response functions of agregate credit and banking indicators to a negative bank leverage shock (with 70 percent confidence intervals).

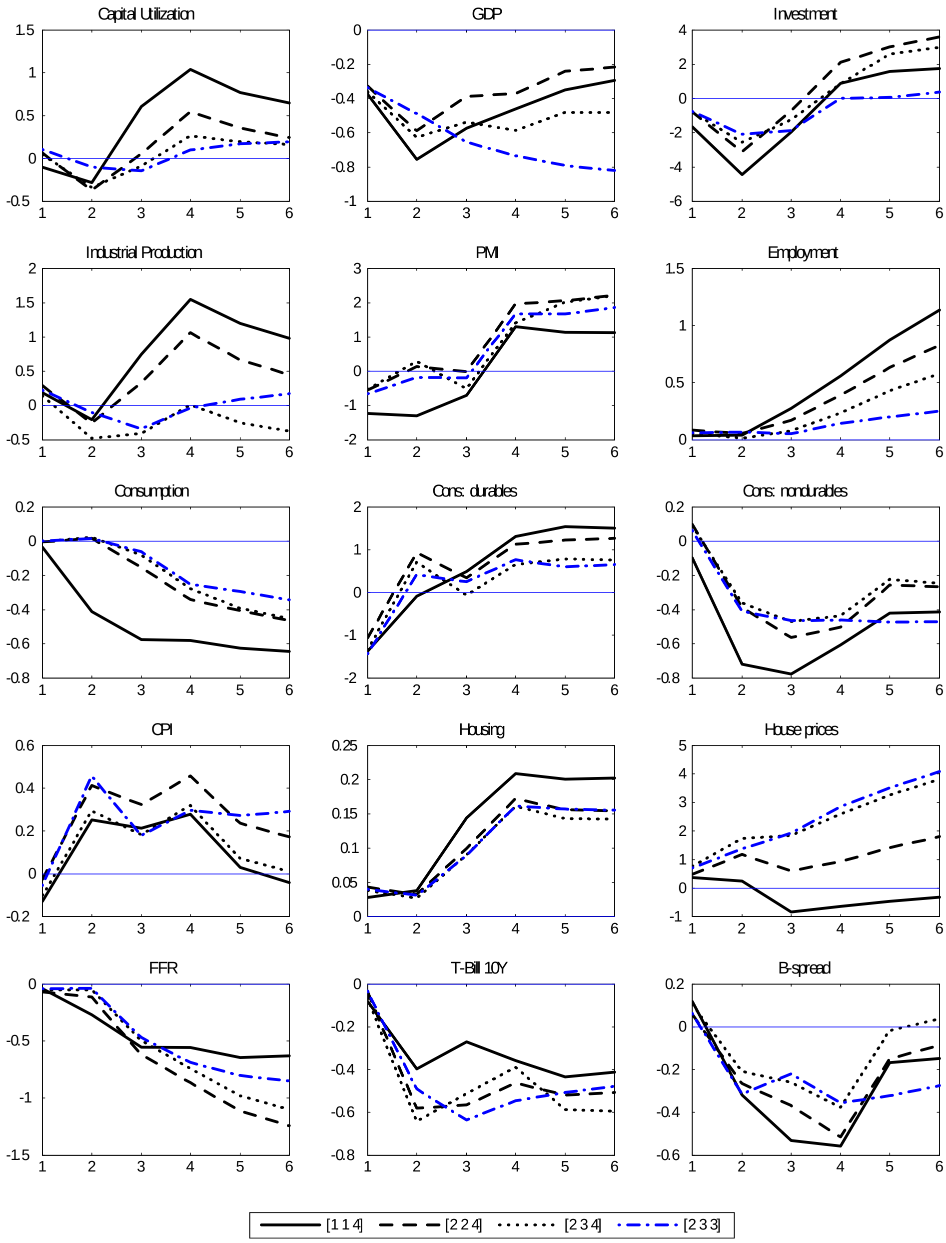

Figure 6: Robustness to FADL specification choices: responses of selected macro variables to a positive bank capital ratio shock assuming different lag selection in the FADL regressions ([1 1 4] means one lag for the autoregressive part, one for each of the macro shocks and four for the capital ratio shock).

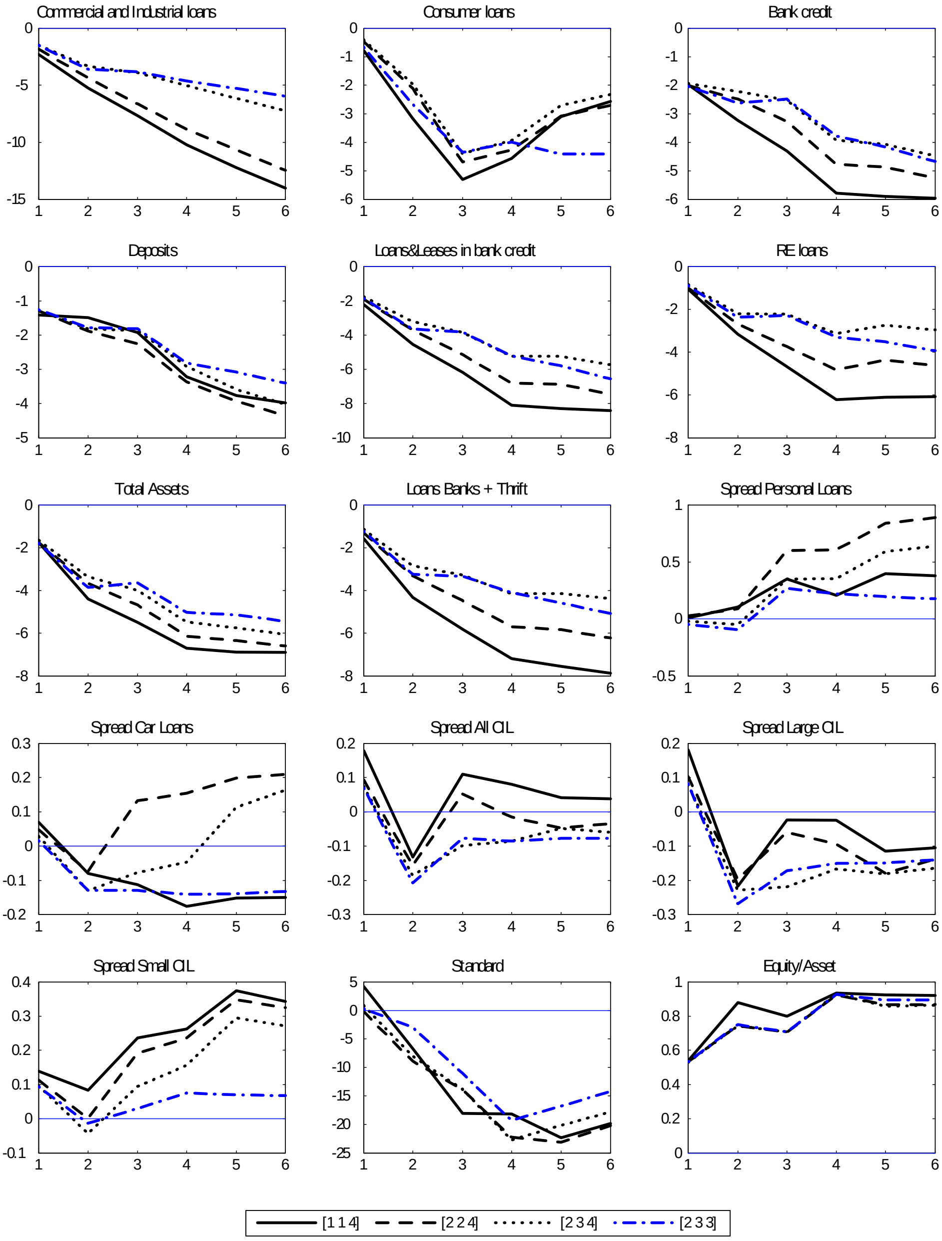

Figure 7: Robustness to FADL specification choices: responses of credit variables to a positive bank capital ratio shock assuming different lag selection in the FADL regressions ([1 1 4] means one lag for the autoregressive part, one for each of the macro shocks and four for the capital ratio shock).

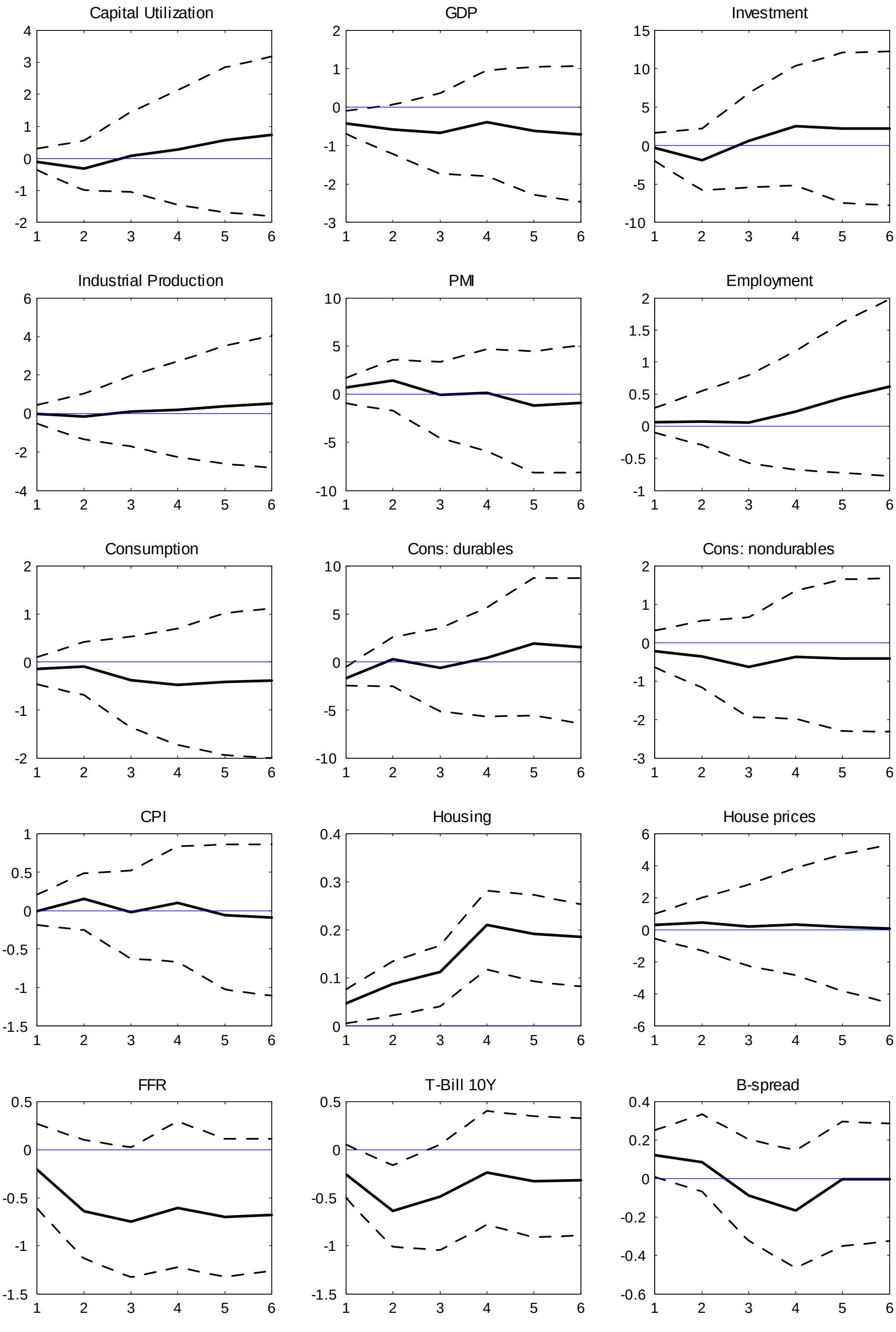

Figure 8: Impulse responses of macroeconomic variables in X_t to a negative bank leverage shock, estimated over the pre-crisis period (up to 2008 Q2, with 70 percent confidence intervals).

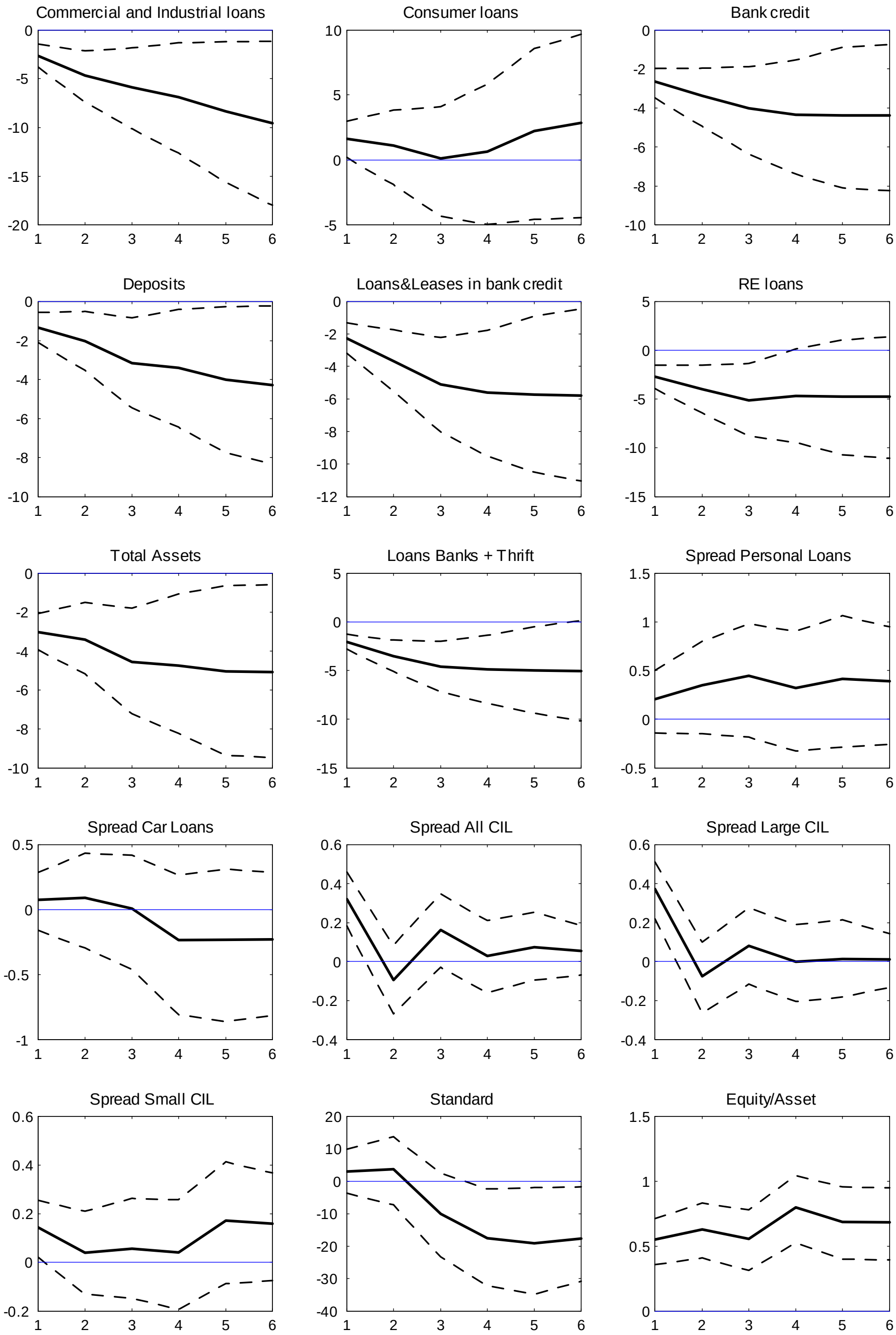

Figure 9: Impulse responses of credit and banking indicators to a negative bank leverage shock, estimated over the pre-crisis period (up to 2008 Q2, with 70 percent confidence intervals).

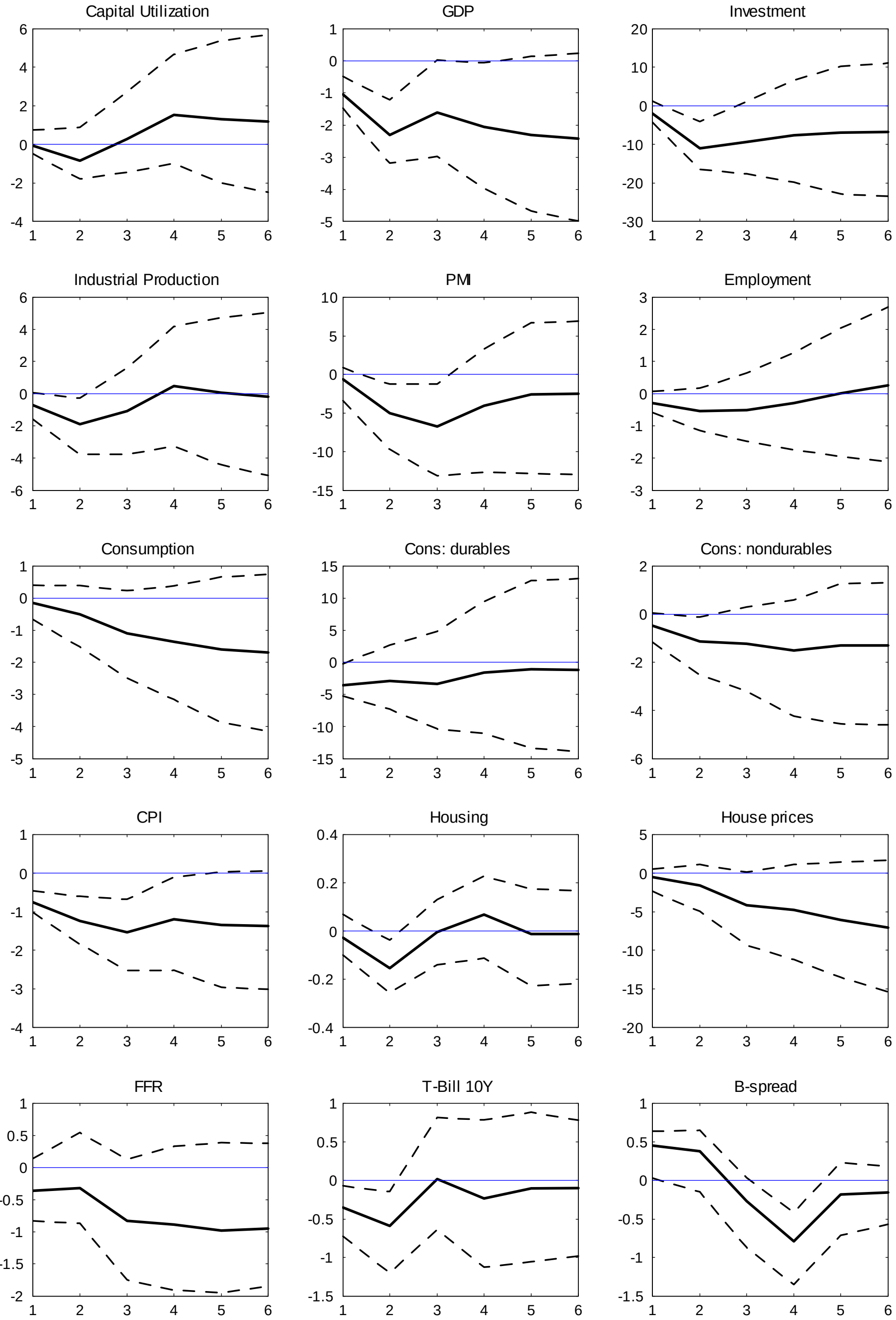

Figure 10: Impulse response functions of macroeconomic variables in X_t to an asymmetric shock reducing bank leverage (with 70 percent confidence intervals)

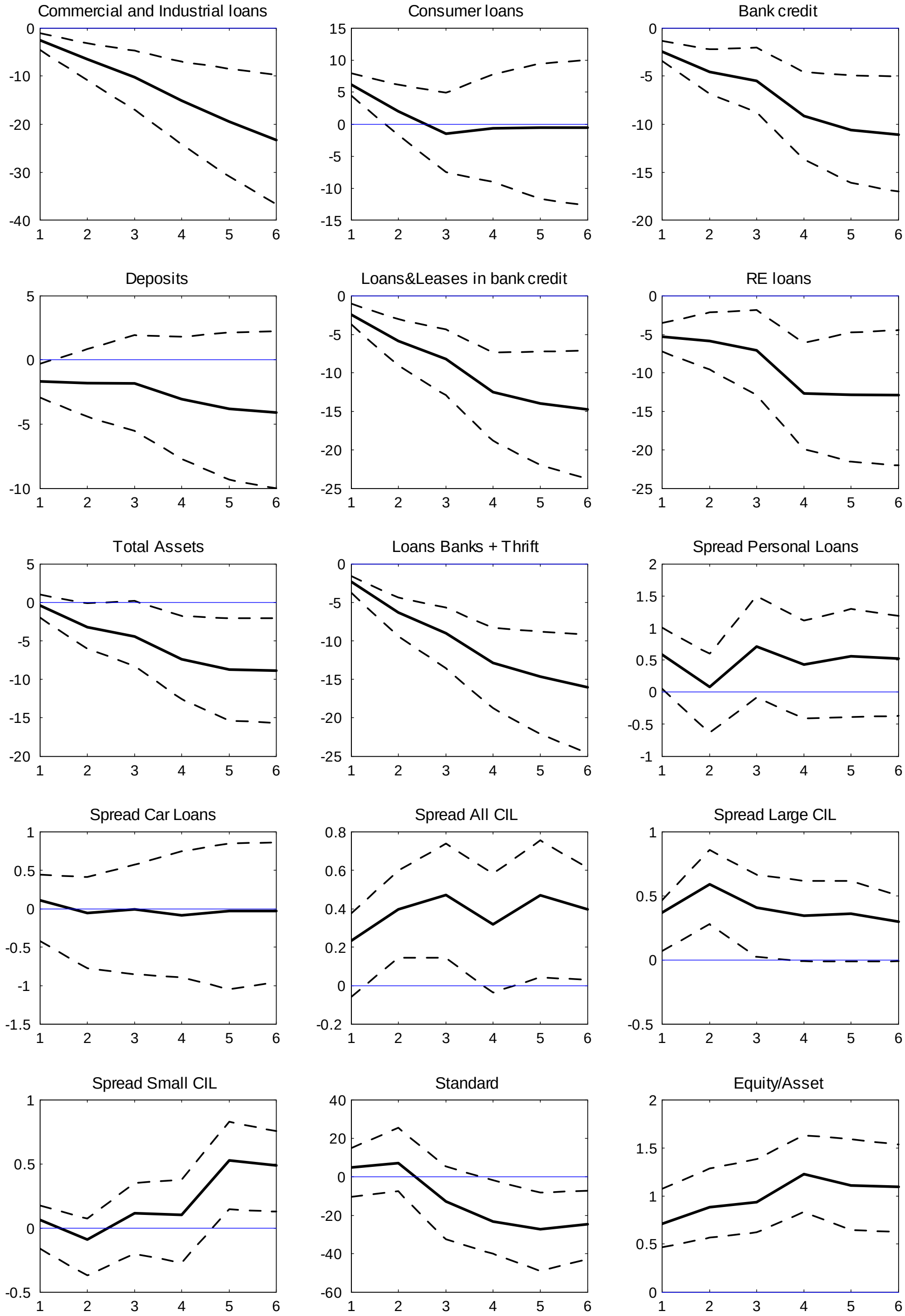

Figure 11: Impulse response functions of agregate credit and banking indicators to an asymmetric shock reducing bank leverage (with 70 percent confidence intervals).

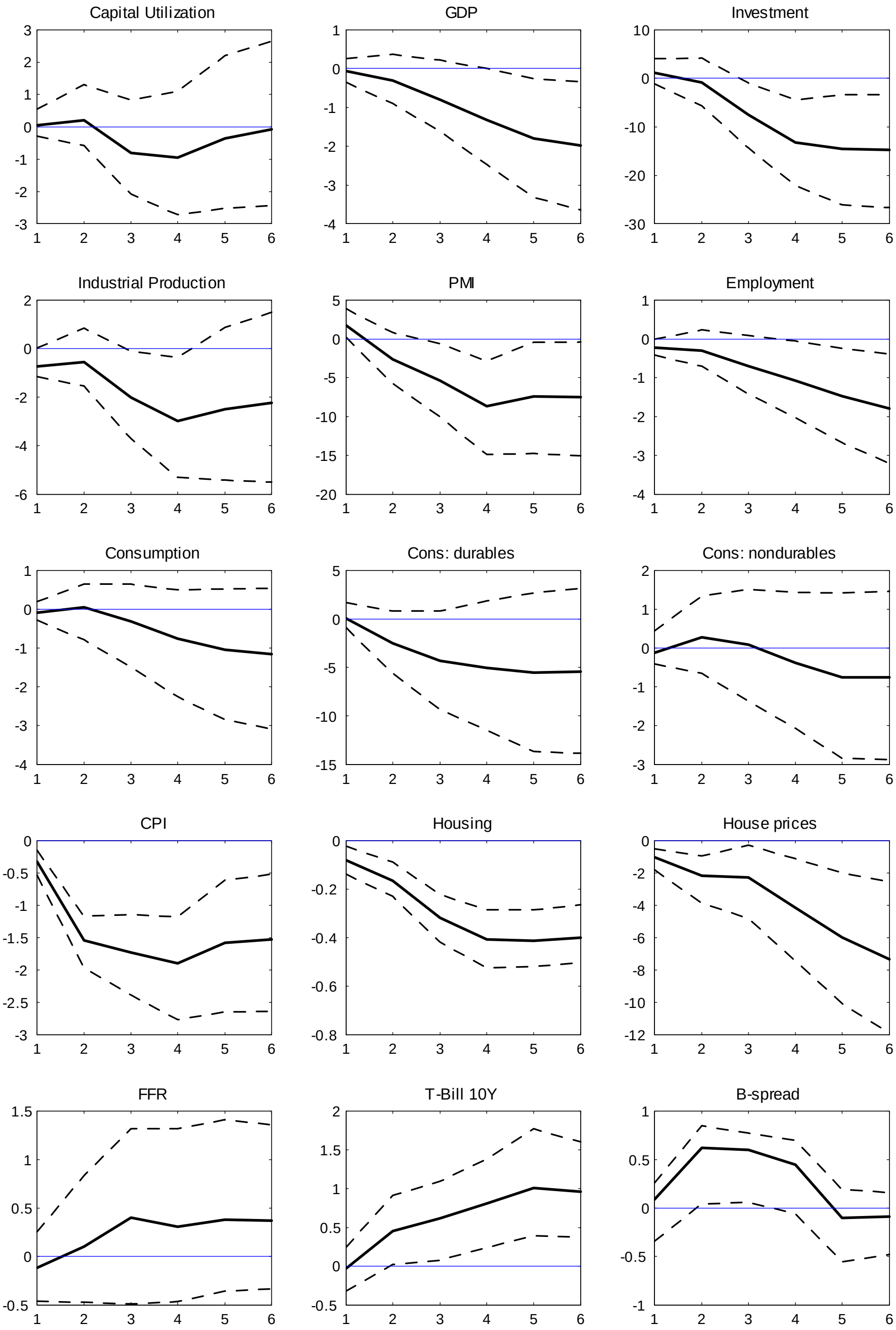

Figure 12: Impulse response functions of macroeconomic variables in X_t to an asymmetric shock increasing bank leverage (with 70 percent confidence intervals)

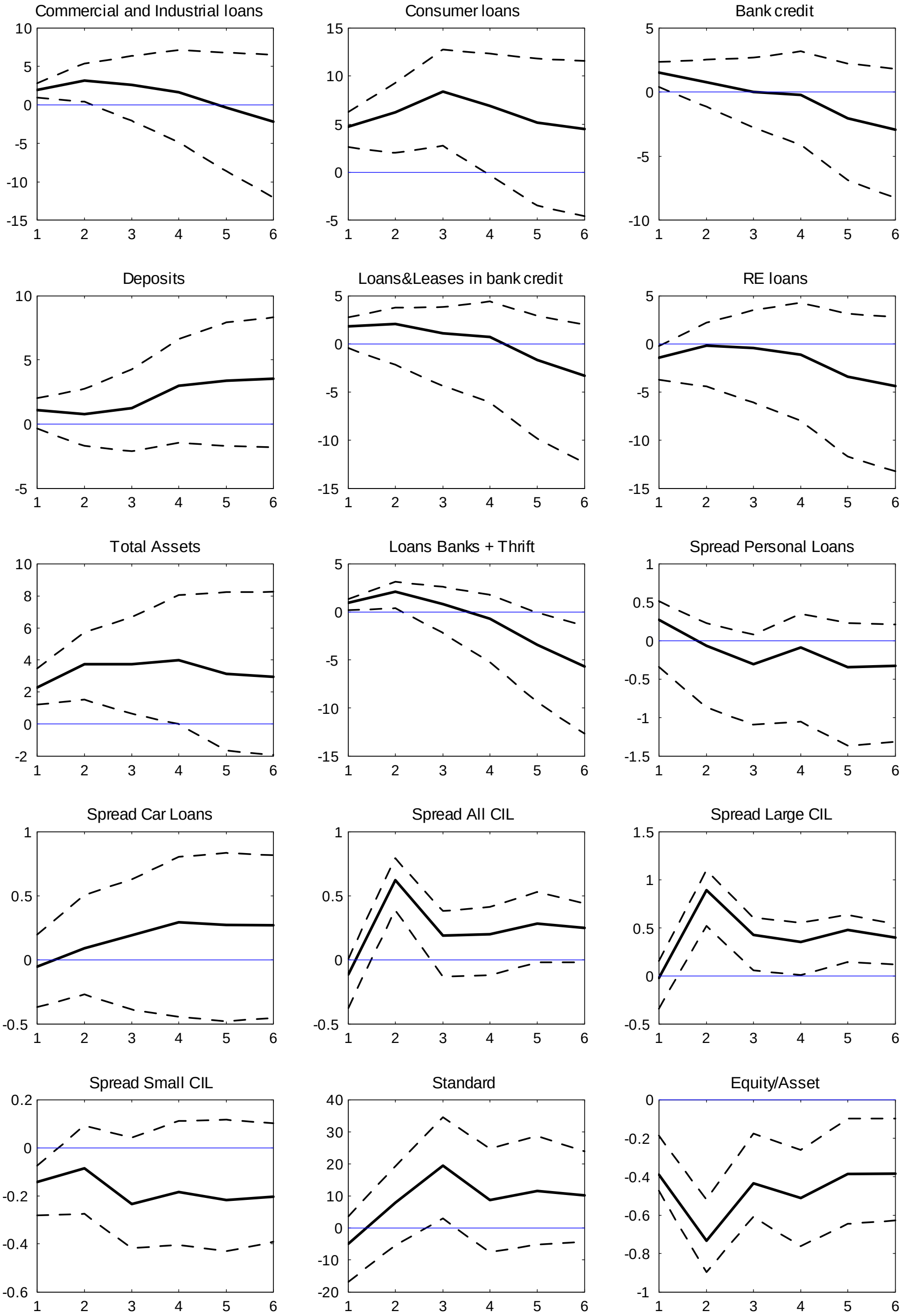

Figure 13: Impulse response functions of agregate credit and banking indicators to an asymmetric shock increasing bank leverage (with 70 percent confidence intervals).

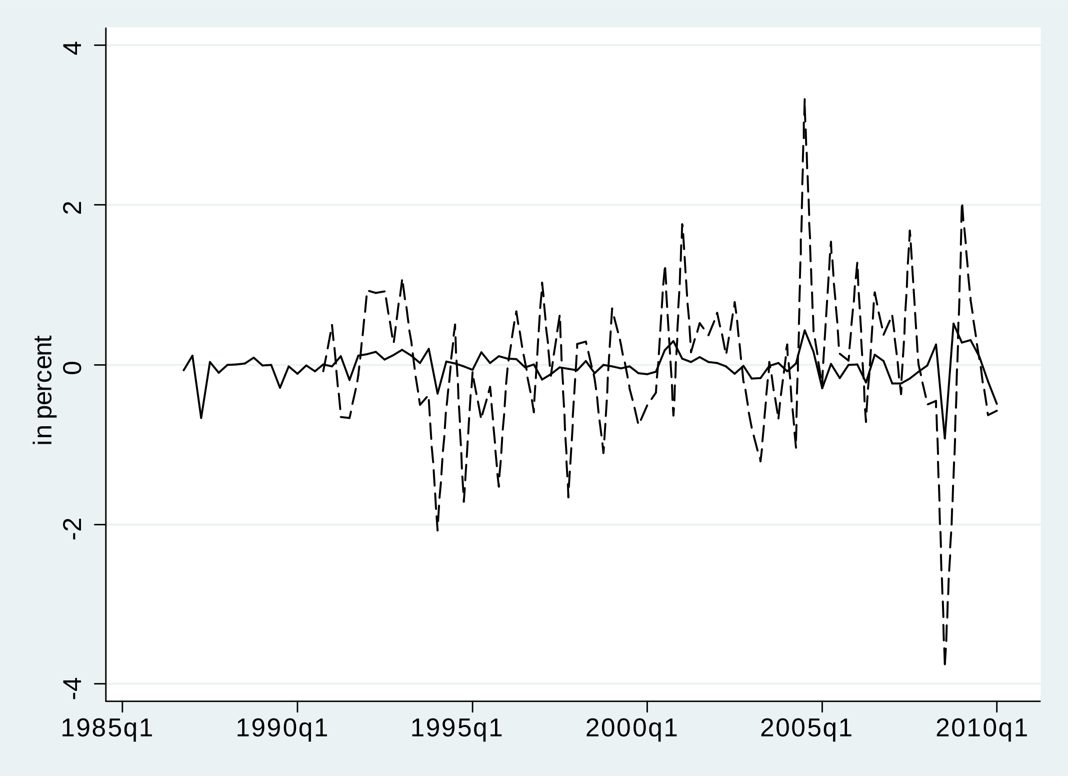

Figure 14: Alternative measures of aggregate bank capital ratio shocks : our measure (solid line) vs BE measure (dashed line).

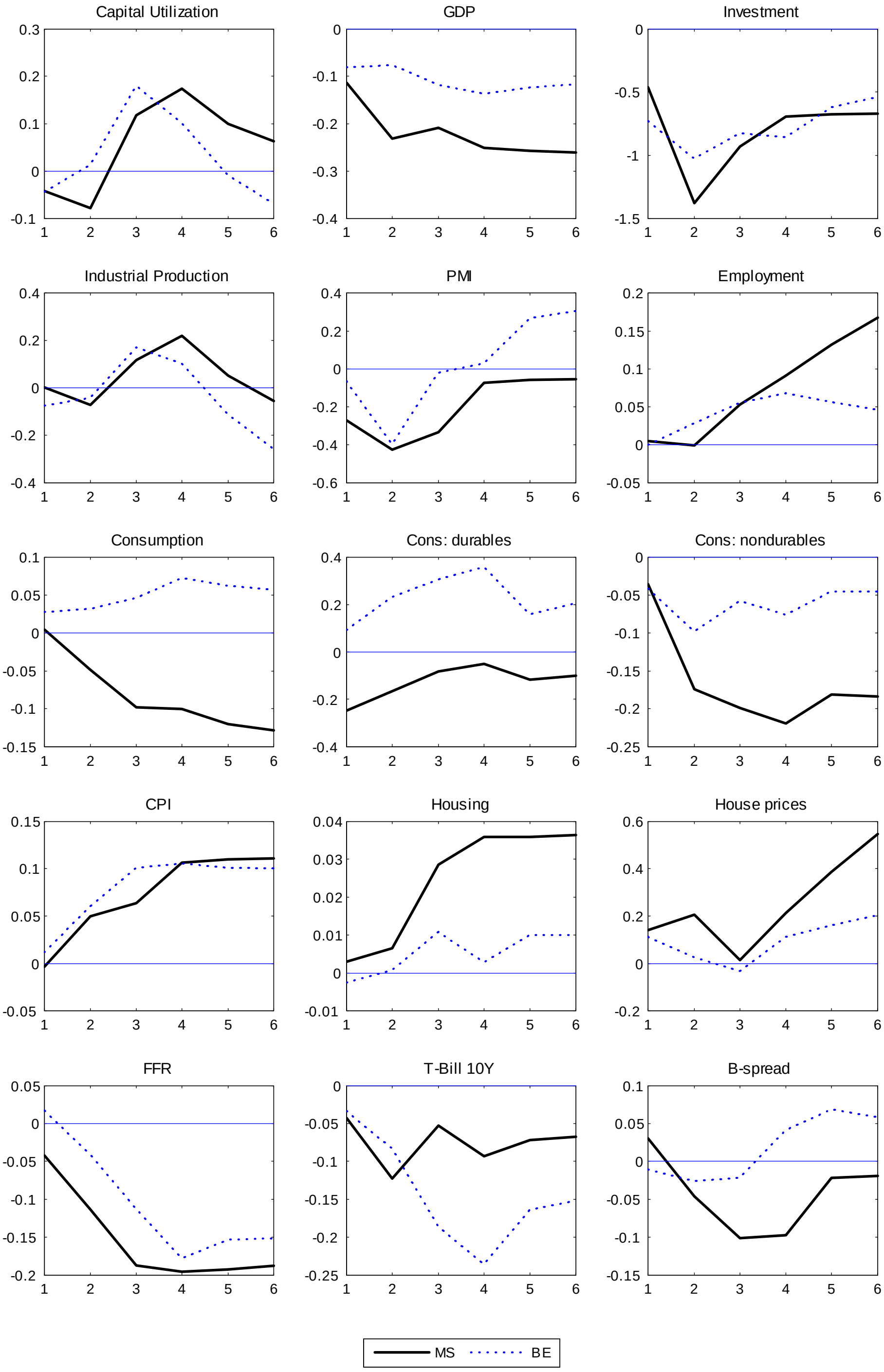

Figure 15: Comparison of responses of non-banking macroeconomic variables to a positive bank capital ratio shock as we estimate it (MS) with responses to the bank capital ratio shock as computed in Berrospide and Edge (2010) (BE). The common period of estimation of the IRFs is 1990 Q4 to 2010 Q1 due to the shorter history of some of the variables used for the estimation of the BE shock.

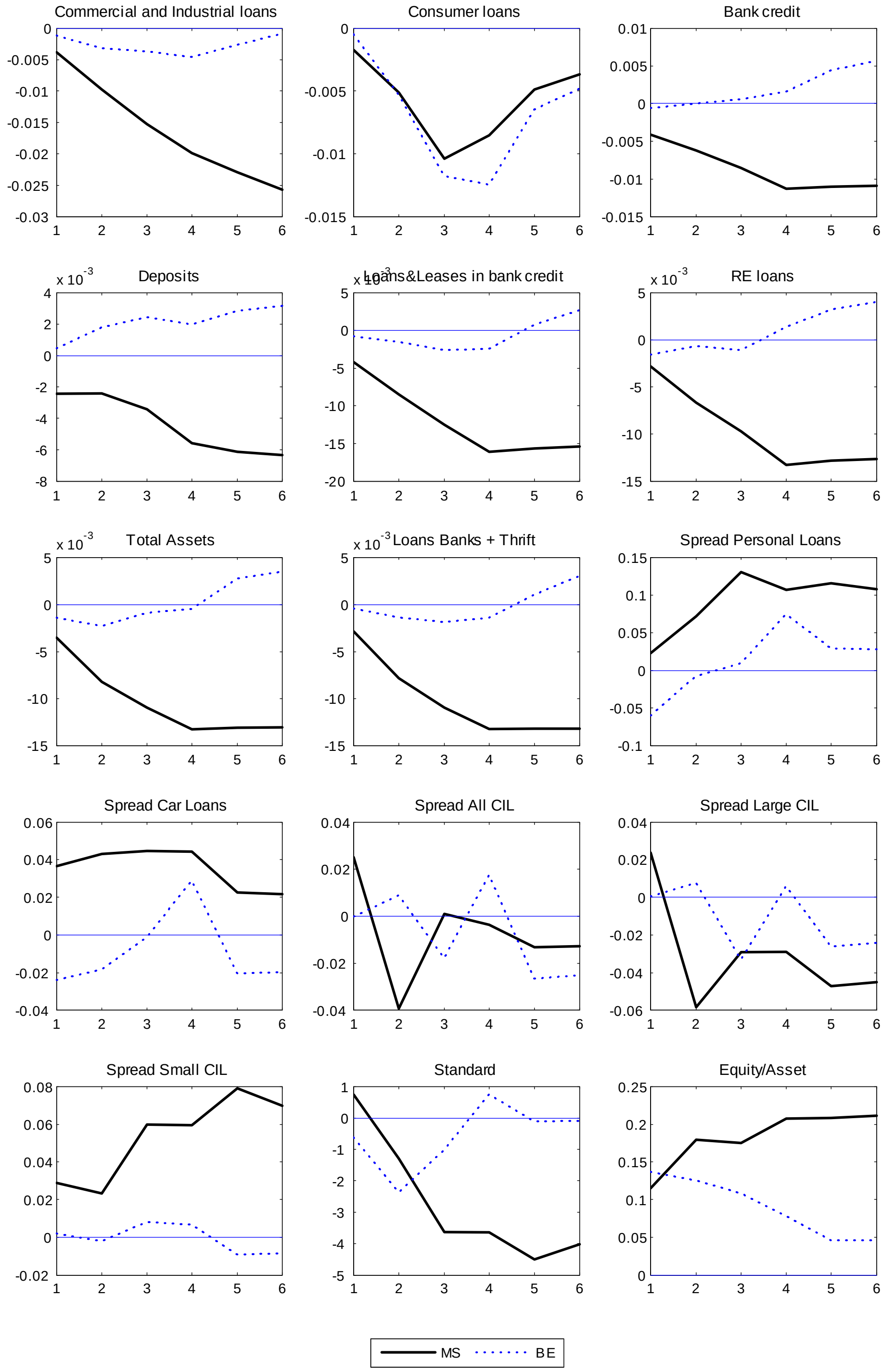

Figure 16: Comparison of responses of credit and banking variables to a positive bank capital ratio shock as we estimate it (MS) with responses to the bank capital ratio shock as computed in Berrospide and Edge (2010) (BE). The common period of estimation of the IRFs is 1990 Q4 to 2010 Q1 due to the shorter history of some of the variables used for the estimation of the BE shock.