THE MACROECONOMIC EFFECTS OF SHOCKS TO LARGE BANKS' CAPITAL

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ABSTRACT. We propose a simple approach to quantifying the macroeconomic effects of shocks to large banks' leverage. We first estimate a standard dynamic model of leverage targeting at the bank level and use it to derive an aggregate measure of the economic capital buffer of large US bank holding corporations. We then evaluate the response of key macro variables to a shock to this aggregate bank capital buffer using standard monetary VAR models. We find that shocks to the capital of large US banks explain a substantial share of the variance of credit to firms and real activity.

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I. Introduction

Do fluctuations in the leverage of large financial institutions matter for explaining macroeconomic activity? Recent analyzes of the credit boom and bust of the last decade suggest that they do.[1] However, while many studies have recently explored the theoretical underpinnings of the relationship between banks' leverage and economic activity [2] and others have documented the cyclical properties of bank balance sheets[3], little is known about the magnitude of the macroeconomic effects of shocks to large banks' leverage. This mostly reflects a measurement problem. As far as banks aim to continuously adjust their actual leverage to a time-varying desired target which depends primarily on their own financial health and business model, micro data are of the essence to properly assess banks' leverage constraints and their effects.[4] However, pure bank-level analyses ignore by nature the possible feedback effects between banks' conditions and the macroeconomy.[5] They are therefore not suited for an evaluation of the aggregate consequences of bank leverage shocks for the business cycle.[6]

In this paper, we propose a simple approach to assessing the macroeconomic consequences of a shock to the leverage constraints of large US bank holding companies (BHCs). The specificity of our framework is how we combine disaggregated information on the balance sheets of large banks and macroeconomic aggregates. We define bank leverage as the ratio of equity capital to unweighted assets and measure the severity of a bank's leverage constraints as the gap between its actual and desired capital ratios. This gap, which we refer to as capital buffer, is however unobserved and has to be estimated. We exploit an unbalanced panel of balance sheet ratios for some 100 US large bank holding companies over the period from 1990 to 2013 to estimate individual bank capital buffers, and then aggregate them to construct a relevant macroeconomic measure of the capital buffer of large US banks, the ABCB (for Aggregate Bank capital Buffer). We then look at the responses of key macroeconomic variables to a shock affecting this aggregate bank capital buffer within a standard monetary Vector Auto-regressive (VAR) model. Depending on model specifications, we find that shocks to the leverage of large US banks explain between a tenth and a fifth of the variance of credit to firms as well as of the variance of the corporate credit spread, and up to 6% of the variance of US GDP after one year.

[1]For instance, Adrian and Shin (2010) find that large investment banks tend to increase their leverage in expansion phases, when asset prices are booming and the volatility of asset prices is low, which tends to push asset prices further up. Adrian et al. (2013) also show that the book leverage of these institutions has a strong predictive power for asset prices.

[2]See for example Meh and Moran (2010), Gerali et al. (2010), Adrian and Boyarchenko (2012), He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014).

[3]See, e.g., Mimir (2015), Laux and Rauter (2014).

[4]Covas and Haan (2011) document that it is in general important to look at individual data to describe properly the cyclical properties of firms' debt vs equity financing, while Gropp and Heider (2010) show that standard cross-sectional determinants of non-financial firms leverage are also relevant for banks.

[5]See e.g., Bernanke and Lown (1991), Peek and Rosengren (2000), and, more recently Puri et al. (2011)

[6]Ashcraft (2006) and Meeks (2015) similarly call for solutions bridging the gap between micro and macro in order to better evaluate the business cycle consequences of banking shocks.

Our approach to banks' leverage constraints assumes that banks, like other types of companies, dynamically adjust their capital-to-assets ratio in order to meet a pre-specified target level.[7] Banks are highly regulated companies and in particular large BHCs in the US have been subject over the last three decades to the Basel I, then Basel II capital requirements. Nevertheless, the view is widely held that regulatory constraints on large banks' leverage ratio have not been much binding since the early 1990s, which suggests that their actual leverage ratio has been largely determined by market's discipline over the recent decades (see for instance Flannery and Rangan, 2008; and Berger et al., 2008).[8] Consequently, we model a bank's capital buffer as the difference between its actual capital ratio and its estimated economic capital ratio, which reflects the risk aversion of creditors and the risk exposure of the institution. This desired level of economic capital may fluctuate with the business and financial cycles, but it is reasonable to assume that a bank cannot adjust immediately its actual ratio to a new desired level because the required balance sheet adjustments entail costs. Following a standard approach (cf., Hancock and Wilcox, 1994; Kashyap and Stein, 2000; and more recently Berrospide and Edge, 2010), we therefore posit a dynamic adjustment model of an individual bank's capital ratio, that we first estimate using a panel regression with bank fixed effects. Assuming that the unobserved targeted capital ratio each period depends on both fixed effect and observable bank-specific and macro determinants, we retrieve bank-specific series of time-varying capital buffers. We then define the Aggregate Bank Capital Buffer each period as the average value of estimated individual buffers across all banks, weighted by the relative size of the institutions. Our approach is therefore similar to the way Bassett et al. (2014) construct their aggregate measure of credit supply from shocks to individual banks' responses to the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS).

The resulting aggregate measure of large US banks' capital buffer fluctuates widely over the last two decades and a half. Notably, the ABCB drops during each of the three recessions of the period, and stays each time in negative territory for a couple of years after the recession ended. This suggests that our measure is a plausible indicator of aggregate capital shortages in the banking system. As we are interested in the consequences of changes in the ABCB for credit provision to the economy, we first look at how our measure relates with other popular measures of credit conditions and credit supply, like bond credit spreads, the tightening index from the Fed's SLOOS, and the share of bank loans made under commitment. We find that the ABCB strongly comoves with these indicators. Indeed, it predicts most of them, but is also Granger caused by most of them.

[7]Studies showing that firms try to adjust to time-varying leverage targets include Leary and Roberts (2005) and Flannery and Rangan (2006). For BHCs, see also Berger et al. (2008) and Hancock et al. (1995).

[8]Since the early 1990s, large BHCs must operate with a Tier 1 to unweighted capital ratio of 3% to 4%, depending on institution's specifics. In practice, all of them post higher ratios. In our panel, the median ratio of equity capital to total assets (a somewhat more restrictive measure of leverage as the regulatory one) is 8.25% and 90% of observations are above 6%. This preeminence of economic over regulatory leverage constraints may reflect some important regulatory changes that were introduced at that time, notably the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991, which contributed to reduce perceived implicit government guarantees in case of bank failures (Flannery and Rangan, 2008), but also the stronger focus of the Basel regulations on other measures of adequate capitalization.

We then plug the ABCB series into a small-scale monetary VAR model together with relevant macro and financial variables, in order to estimate the effects of a negative bank capital buffer shock on economic activity while accounting for possible feedback effects between aggregate bank leverage and the macroeconomy. We find robust evidence that our aggregate measure of the capital buffer of large US banks matters for understanding fluctuations in credit aggregates as well as the US business cycle. In particular, an unexpected drop in the banking system's capital buffer by 1 percentage point triggers a significant and persistent fall in the growth of bank credit to firms, as commercial and industry loans contract by some 6 percent after one year. On the real activity side, GDP growth also significantly falls, with a maximum impact reached after 2 quarters.

These results prove robust to a series of alternative specification choices. In particular, we construct an alternative measure of the ABCB, allowing for some heterogeneity across banks in the relationship between the bank capital ratio and its determinants. Indeed, since the size distribution of US BHCs is very skewed, even among the 100 largest companies, one may reasonably argue that larger banks in the sample may be quite different from smaller banks, and therefore might react in a different way to, e.g., changes in macroeconomic forecasts or financial volatility (a dynamic heterogeneity which is not captured by the bank fixed effects). We find that this "heterogeneity-adjusted" ABCB delivers similar results as before. The estimated macro impact of a shock on bank leverage is even slightly stronger. We also check that our main conclusions still hold when we change the specifications of the baseline VAR model along several dimensions, including the ordering of the endogenous variables and the preferred measure of real activity.

Our study fits in the rapidly expanding literature which aims at quantifying the consequences of financial frictions and financial shocks for economic activity. More precisely, it first relates to a strand of empirical studies that look for new aggregate indicators to be included as instruments in reduced-form monetary macro models 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 credit aggregates. Examples of this approach are provided by Lown and Morgan (2006), Morgan (1998) and Peek et al. (2003).[9]

Second, our paper also relates to a few recent contributions that try to exploit microeconomic information in order to improve the identification of financial shocks in a macroeconomic setup. The closest to our study is the paper already mentioned by Bassett et al. (2014), who construct an aggregate summary series of bank-level innovations to lending standards and use it to identify bank credit supply shocks in a small monetary VAR of the US economy. Building

[9]Peek et al. (2003) instrument credit by the share of assets held by banks falling into the "CAMEL 5" bucket (i.e. viewed by the US banking regulator as likely to fail in the coming quarters). Morgan (1998) looks 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. Lown and Morgan (2006) 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.

on information from bank lending surveys indeed looks as a promising avenue, since, by construction, the decomposition between developments in credit demand and supply is given by respondents.[10] However, the aggregate credit supply indicator obtained by Bassett et al. (ibid.) is silent about the source of the credit supply shock.[11] In contrast, our study focuses on the macroeconomic consequences of credit supply shocks associated with unintended changes in the leverage constraints of large banking institutions. Other innovative approaches relying on a mix of micro and macro data include Meeks (2015), Amiti and Weinstein (2013) and Buch and Neugebauer (2011). Meeks (2015) exploit bank-level information on time-varying regulatory capital ratios in the UK to sharpen the prior distributions of parameters linking aggregate bank capital and aggregate bank credit in a macroeconomic Bayesian VAR. Amiti and Weinstein (2013) and Buch and Neugebauer (2011) build on the theory of the granular origins of business cycle fluctuations recently proposed by Gabaix (2011). Amiti and Weinstein (2013) use matched bank-firm lending data for Japan and decompose aggregate loan fluctuations into bank, firm, industry, and common shocks and find that bank supply shocks explain 40 percent of aggregate loan and investment fluctuations in Japan over the period 1990-2010. Buch and Neugebauer (2011) compute "granular credit residuals" at the country level for a panel of industrial economies, using annual bank-level information from Bankscope. This granular residual is computed as the size-weighted average across banks in a country of estimated idiosyncratic credit innovations, which echoes the way we construct our ABCB indicator. They find that idiosyncratic changes in the volume of credit granted by the few largest banks in each country matter for explaining domestic business cycle fluctuations. Last, a series of recent papers, such as Jimborean and Mésonnier (2010) and Buch et al. (2014), try to bridge the gap between bank-level and macroeconomic information by augmenting a VAR with statistical factors extracted from disaggregated bank-level datasets. None of these papers however deals with the macro consequences of bank leverage shocks.

The rest of the paper is organized as follows. Section **II** explains how we construct our aggregate measure of banks' capital buffer for the US. Section **III** investigates how this ABCB relates to standard measures of bank credit supply and presents our VAR analysis of the business cycle consequences of a shock to large banks' leverage constraints. Finally, section **IV** concludes.

II. An aggregate measure of the capital buffer of large US bank holding companies

In this section, we explain how we construct an aggregate measure of the capital buffer of large banking institutions. Our modeling approach proceeds in two steps. Using a large panel of banks' balance sheets, we first estimate a partial adjustment model of individual bank capital-to-assets ratios in order to filter out estimates of banks' desired capital ratio. We thus obtain a panel of estimated bank capital buffers – the difference between the observed and the desired ratios–, that we then aggregate into our macroeconomic measure of bank capital buffer. We

[10] I.e., to the extent that reporting bank officers know and tell the truth.

[11] An identified tightening may indeed reflect binding capital constraints as well as liquidity shortages, or any other source of credit supply contraction.

first present below the empirical model of bank capital, our sample of large US BHCs and the estimation results of the panel regressions. We then detail how we aggregate estimated individual buffers into an enonomy-wide indicator that is suitable for macroeconomic analysis.

A. A simple dynamic model of bank leverage targeting

We first estimate a dynamic model of bank capital-to-assets ratios in order to retrieve a panel of bank capital buffers 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 a bank's managers cannot immediately adjust its (unweighted) capital ratio towards their (time-varying) target.[12] 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:

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

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 $\varepsilon_{i,t}$ a bank-specific innovation to leverage. 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 macroeconomic or macro-financial variables M_t, so that:

$$k^*_{i,t} = \alpha_i + \theta_Z Z_{i,t} + \theta_M M_t. \tag{2}$$

The macro variables aim here to capture fluctuations in macro risks that bankers would take into account in their capital decisions. Note that by construction the target level of bank capital is akin to an "economic" capital requirement, not a regulatory one.

Replacing for $k^*_{i,t}$ in equation (1) and rearranging, we get our empirical model for individual bank capital ratios, that we estimate using standard panel regression techniques, as detailed below:

$$k_{i,t} = \tilde{\alpha}_i + \tilde{\beta} k_{i,t-1} + \tilde{\theta}_Z Z_{i,t-1} + \tilde{\theta}_M M_{t-1} + \varepsilon_{i,t} \tag{3}$$

where $\tilde{\alpha}_i = \lambda \alpha_i$, $\tilde{\beta} = 1 - \lambda$, $\tilde{\theta}_Z = \lambda \theta_Z$ and $\tilde{\theta}_M = \lambda \theta_M$. From this regression, we retrieve estimates of the target capital ratios, $\hat{k}^*_{i,t}$, and finally derive estimates of the bank-specific capital buffers, $cb_{i,t}$:

$$cb_{i,t} = k_{i,t} - \hat{k}^*_{i,t}. \tag{4}$$

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

B. Bank-level data

We detail here how we construct our dataset of individual bank balance sheets and estimate the individual capital buffers. 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.[13] In the following, we use the generic term "banks" to denote the BHCs in our sample. Our bank database covers the period from 1990 Q1 to 2013 Q4. Notably, the period of study thus covers the years of implementation of the first Basel capital regulations (post 1988) and 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 capital ratios and buffers to have happened with potentially significant macroeconomic consequences.

The raw database of FRY-9C filings requires some preliminary cleaning for our purpose. Indeed, 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 shrank, while the size and complexity of the larger companies increased dramatically.[14] The raw database is therefore highly unbalanced, with only a minority of banks being 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 32 institutions fell into this category and stopped their reporting at this date, the total cumulated assets of the reporting banks dropped by some 30% in early 2006.

Taking these features of the initial balance sheet database into account, we design 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 exhibit relatively similar capital policies, so that running a panel regression on our set of institutions would make sense. We thus keep only the banks whose total assets always remained above $3 billion. Second, we are 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 exclude 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 delete bank subsidiaries affected by the

[13] Houston et al. (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.

[14] See Avraham et al. (2012) and Copeland (2012) for detailed accounts of changes affecting the population of US BHCs over the last two decades

change in reporting guidelines mentioned above so as to avoid any double counting, as well as three large BHCs affiliated to foreign parent companies.[15]

As said, a number of mergers and acquisitions have affected the US banking system since the early-1990s. We used the Chicago Fed database on M&A involving BHC to identify bank-quarter observations when such operations took place. Some 400 M&As happened in our sample over the period of study. To avoid introducing arbitrary noise in our estimate of bank-level capital targeting behavior, 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 too small a number of consecutive observations. Instead, we deal with M&As by dropping affected observations of acquiring banks when running the panel regressions presented below.[16]

Our sample finally consists of 103 large BHCs that represent on average 76 percent of the total assets in the US banking sector.[17] Although the representativeness of our sample varies somewhat (between 48 percent and 88 percent of the total), it remains relatively high throughout compared to similar studies. Note that of the 103 selected institutions only 26 remain present over the whole sample period, while on average 64 institutions are present in the cross section at each date.

C. Estimation of the panel regression

We present in this section the results of the estimation of the bank-level regression (3), that we repeat here for convenience:

$$k_{i,t} = \tilde{\alpha}_i + \tilde{\beta} k_{i,t-1} + \tilde{\theta}_Z Z_{i,t-1} + \tilde{\theta}_M M_{t-1} + \varepsilon_{i,t} \quad (5)$$

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 lens 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 possible shifts in the banks' business models.

Table 1 reports summary statistics for the bank-specific variables used in the panel regressions. The average institution in our sample is already quite large, with assets above \$ 105

[15]These three foreign BHCs removed from our sample are ABN AMRO North America, Inc., BBVA Compass Bankshares, Inc., and Santander Bancorp.

[16]We also delete a few bank-quarter observations with changes in a bank's total assets by more than 50% in absolute terms that are not associated with a know M&A (8 such outlier observations are detected).

[17]See the Appendix for the complete list of banks in our selection.

billion. Nevertheless, some substantial degree of heterogeneity in size remains in the sample, as the 10 percent largest institutions have (average) assets above \$212 billion, while the 10 percent smallest have 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 at 9 percent, which corresponds to a leverage of about 11 for the average bank. Overall, loans to non-financial clients make up some 60 percent of the total in the average bank's balance sheet, with mortgage loans representing in turn about a half of all loans, and C&I loans only a quarter of them. Average profitability, as reflected by our measure of ROA, is 2.81 percent, which is broadly in line with the average ROA for all US commercial banks over the long-run.[18] Net charge-off rates, which we take as a proxy for the riskiness of bank assets, are at 1.1 percent 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 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 a list of macro control variables in the M_t vector. First, we take real-time measures of expectations regarding 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 rate of growth of real GDP over the coming four quarters, (2) the expected variation in the short-term rate of interest (the rate on 3 month T-Bills) as a proxy for the expected change in monetary policy rates. Second, we include a real-time measure (also taken from the Phil Fed's SPF vintages) of lagged yearly real GDP growth, as well as the spread between Moody's BAA corporate bond yield and the 10-year Treasury yield as a measure of credit risk. Lastly, we take the log of the realized volatility of the S&P500 index as a measure of uncertainty on the US equity market.[19] Table 2 provides some descriptive statistics for this set of macro controls.

Table 4 presents the estimation results of equation (3). A constant and three seasonal dummies are included in the regression but not reported. We estimate the dynamic model of bank leverage using OLS regressions with bank fixed effects ("within" estimator) as suggested by preliminary Hausman tests, and cluster standard errors at the bank-level to correct for possible within-individual correlation of innovations .[20] 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 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

[18]According to call report information compiled by the Federal Reserve, the long-run average ROA for all US commercial banks (on an unconsolidated basis) is close to 4 percent, while the long-run average ROA for the largest banks (here with assets greater than \$15 billion) is about 1 percent.

[19]Our quarterly measure of realized stock market volatility is the standard deviation of daily returns of the market index over a quarter.

[20]Using instead the Huber-White robust estimator of variance does not make any noticeable difference.

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 4 presents the results when only bank-specific variables are included as regressors. Column (2) shows the impact of also including observable macroeconomic variables. The full specification in column (2) is our baseline model in the following. However, a concern could be that, even in a sample of relatively large BHCs as ours, smaller and larger bank corporations would not react the same way to macroeconomic forecasts or other changes in determinants of their targeted leverage, so that the parameter restrictions implicit in this baseline panel regression would not be vindicated. To investigate this issue, columns (3) to (6) present estimation results when the panel regression is run separately for each quartile of the distribution of the selected banks ranked by their average relative size. Some heterogeneity across size quartiles is revealed in estimated coefficients. For robustness, we therefore construct an alternative measure of the individual, and hence the aggregate, bank capital buffer, using coefficient estimates from these four ancillary regressions to recover the unobserved capital ratio targets $\hat{k}^*_{i,s,t}$, where s stands for the size quartile of bank i.

Back to our baseline 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. Looking at the role of bank-specific covariates, we find a positive correlation between capital ratio and bank size, in line with previous results of Berrospide and Edge (2010), who also restrict their sample to the largest US BHCs. [21] Also, banks with a higher share of mortgage loans on their books tend to maintain a higher leverage, which may reflect the lower regulatory capital weight of mortgage loans compared to other risky assets. Neither the lagged ROA nor the lagged ratio of net charge-offs to assets are significant, except in the case of banks in the second quartile (medium-small BHCs). Among the observable macroeconomic controls, three of them are highly significant. An expected rise in GDP growth is associated with a decrease in capital ratios, which hints at a procyclical behavior of bank leverage. In contrast, higher corporate bond credit spreads 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. Last and as in Berrospide and Edge (ibid.), a higher volatility of stock market returns implies on average a lower capital ratio, which may reflect higher capital losses in times of stress.

D. Aggregation

The aggregate bank capital buffer, denoted $ABCB_t$, is obtained as the sequence of cross-sectional weighted averages of the estimated individual capital buffers:

[21]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. Cf., for instance, Kashyap and Stein (1995) and Kishan and Opiela (2000). 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 pick up in this study.

$$ABCB_t = \sum_{i=1}^{\widetilde{N}_t} w_{i,t-1}.cb_{i,t} \tag{6}$$

where $w_{i,t-1}$ 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. Note that including seasonal dummies in the panel regression (3) as we did above does not wipe out seasonal effects from the reconstructed individual capital buffers $cb_{i,t} = k_{i,t} - \hat{k}^*_{i,t}$, let alone from the aggregate ABCB. Since we are ultimately interested in looking at correlations between the ABCP and seasonally adjusted macroeconomic series (like quarterly GDP growth), we finally adjust it by regressing out the impact of four quarterly dummies, and adding the average quarterly effect to the residual.

Weighting the individual capital buffers $cb_{i,t}$ by a measure of the relative size of the banks is important here since we aim to construct a measure that is macroeconomically meaningful: intuitively, the macro consequences, if any, of a 1 percentage point individual capital shortfall should not be the same when the bank totals \$200 billion of assets or when the bank holds less than \$10 billion.[22] We take the lagged share of total banking assets as weights, instead of the contemporaneous share, to limit endogeneity issues.[23] Last, we checked that weighting the individual $\widehat{\varepsilon}_{i,t}$ residuals by each bank's share in total banking loans instead of its share in total banking assets in the sample did not affect our measure of the aggregate bank capital buffer. This is not surprising as average total assets and average total loans appear to be highly correlated in the cross-section of our sample of banks.[24]

While we take the (seasonally adjusted) $ABCB_t$ as our baseline measure of the aggregate bank capital buffer, we also construct for robustness an alternative measure that accounts for a possible heterogeneity across bank size classes in the parameters of the capital adjustment model (3). This alternative measure, $ABCB_t^{het}$, is computed as:

$$ABCB_t^{het} = \sum_{s=1}^{4} \sum_{i=1}^{\widetilde{N}_t} w_{i,t-1}.cb^s_{i,t} \tag{7}$$

where $cb^s_{i,t} = k_{i,s,t} - \hat{k}^*_{i,s,t}$ is the estimated capital buffer for an individual bank i belonging to size quartile s.[25]

Figure 1 presents the two versions of our aggregate bank capital buffer indicator, $ABCB_t$ and $ABCB_t^{het}$. The two are strongly correlated, although the heterogeneity-consistent version shows

[22] Buch et al. (2014) and Bremus et al. (2013) provide empirical evidence that credit developments in major economies are indeed granular, i.e., shocks affecting the largest players explain a substantial part of the volatility of aggregate credit.

[23] Of course, as our panel is unbalanced, this weighting scheme entails that some pure composition effects may affect the constructed aggregate capital buffer. 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 series of the aggregate bank capital buffer weighted by the contemporaneous asset shares and checked that our results remained qualitatively unchanged.

[24] Indeed, the correlation coefficient of average total loans and average total assets across selected banks is close to 0.95.

[25] In what follows, we use a seasonally adjusted version of this alternative aggregate indicator, as it is the case with the benchmark series.

somewhat ampler fluctuations before and during the recent financial crisis. The general pattern of the ABCB indicator is in line with the common view that banks are more capital-constrained during recessions. Indeed, the aggregate capital shortfall seems to have been particularly high during the recessions of 1990-1991 and 2007-2009. According to our measure, the banking sector's capital buffer is close to -2% in the early 1990s. It then drops between -3% and -4% after the bankruptcy of Lehman Brothers in September 2008. Meanwhile, the indicator suggests that large US banks faced an economic capital surplus in the 2000s, a finding consistent with the view that credit risk was mispriced and credit too abundant in the period running-up to the subprime crisis of 2007.

III. Assessing the macroeconomic implications of bank capital shocks

In this section, we use our measure of the banking sector's (economic) capital buffer to investigate the macroeconomic consequences of fluctuations in large banks' capital. We first provide evidence that our bank capital buffer indicator is a relevant measure of credit conditions, as it strongly covariates with other standard macroeconomic indicators of credit availability and even predicts some of them. We then analyze the responses of key macro variables to a shock to the bank capital buffer within a standard structural VAR framework.

A. The ABCB and other indicators of credit supply

Our interest in a summary measure of big banks' capital buffer is motivated by the assumption that a banking system that is dominated by capital constrained banks tends to restrict credit provision, at least in the short run. As a first step, it is therefore natural to check that our measure, the ABCB, is correlated with commonly used indicators of credit conditions, such as corporate bond spreads (see e.g., Gilchrist and Zakrajsek, 2012; Gilchrist et al., 2009), measures of credit standards derived from surveys (see e.g., Ciccarelli et al., 2010; Lown and Morgan, 2006) and aggregate measures of the share of bank loans made under commitment (see e.g., Ivashina and Scharfstein, 2010; Morgan, 1998).

Indeed, Figure 2 shows that the ABCB indicator strongly comoves with AAA and BAA corporate spreads, a standard measure of the costs faced on the bond markets by (large) firms of good and medium credit quality respectively[26]. Unconditional correlation coefficients of the ABCB with these spreads are -0.40 and -0.57, respectively, over the period from 1990 to 2013. Capital shortfalls of US large banks therefore tend to be associated with tighter funding conditions for US non-financial firms on wholesale markets, and notably for firms of lower credit quality.

Furthermore, Figure 2 shows that the ABCB is also strongly negatively correlated with tightening credit standards. We show here the most often used summary measure of banks' lending standards: the share of banks reporting a tightening of their standards for C&I loans to

[26]In what follows, we compute bond corporate spreads as the difference between Moody's index of AAA or BAA corporate bond yields and the yield of the 10-year US Treasury bond.

large firms, as reported in the Federal Reserve System's Senior Loan Officer Opinion Survey (SLOOS). The unconditional correlation coefficient of the ABCB with this index is -0.54, but the correlation is even stronger (in absolute terms) with other indicators derived from the SLOOS, as the share of banks reporting a tightening of standards vis-à-vis small firms (coefficient of -0.57) and share of banks increasing spreads of loans rates for small firms (-0.66).

Beyond this visual evidence that the ABCB and common measures of credit conditions tend to comove, at least at low frequencies, we also test for Granger causality between our indicator of banks' capital buffer and other candidate measures. Table 5 presents the results of a series of pairwise Granger causality tests with a selection of credit tightening indicators: (i) corporates spreads as before, as well as (ii) the share of banks tightening their standards for loans to large and small firms and the share of banks increasing their loan interest margin with large and small firms, but also (iii) the share of bank loans made under commitment as reported in the Federal Reserve System's Survey of Terms of Business Lending (E.2 release). We find that all these measures of credit conditions predict the ABCB at the 10 percent level. In turn, the ABCB predicts all measures in the short run, with the exception of the BAA corporate spread. Its predictive power is also the greatest, and significant at the 5 percent level, for three indicators which directly relate to bank lending supply: the indicator of tightening credit standards with small firms, increased loan interest margin with large firms and the share of bank loans made under commitment.

B. VAR analysis

This section quantifies the macroeconomic effects of an exogenous shock to bank capital by including the ABCB into a standard monetary vector autoregressive model (VAR):

$$Y_t = C + \Phi(L)Y_{t-1} + e_t \tag{8}$$

where Y_t is a $K \times 1$ vector of time series, $\Phi(L)$ is a matrix lag polynomial of order p and e_t is a K-dimensional white noise uncorrelated with lags of Y_t. The benchmark model includes the following six endogenous variables: (1) real activity measured as the log-difference of real GDP (GDP), (2) inflation measured as the log-difference of the consumer price index (CPI), (3) the federal funds rate in order to control for the stance of monetary policy (FFR), (4) our aggregate indicator of large banks' capital buffer (CAPITAL BUFFER), (5) the log-difference of commercial and industrial loans (LOANS) and (6) the BAA corporate bond spread (CREDIT SPREAD). As for instance Berrospide and Edge (2010) or Bassett et al. (2014), we therefore simply add here a financial block to the standard 3-variable monetary VAR, which then encompasses a broad measure of bank lending activity, our aggregate bank capital buffer and a credit spread. Including the latter can be justified as a proxy for the external finance premium, which helps to properly identify credit supply shocks (see e.g., Boivin et al., 2013; Gilchrist et al., 2009).

The shock on bank capital in the benchmark VAR is identified using this particular recursive ordering. We assume that real GDP and inflation do not react on impact to an unexpected shock affecting the capital position of large US banks. This sounds plausible even at quarterly frequency given adjustment lags in production and investment plans and price stickiness at the aggregate level. The restriction forbidding an immediate response of the Federal funds rate is vindicated by the assumption that the central bank roughly follows a Taylor rule and mostly responds, on impact, to changes in inflation and the output-gap. It may also reflect the fact that, even if the Fed is concerned with financial stability issues, changes in bank capital would only become known to monetary policy-makers with a lag due to reporting delays. We do not restrict the response of bank loans to a bank capital shock, hence such a shock can elicit an immediate response of bank credit. Finally, as an asset price, the credit spread is likely to incorporate news to any of the preceding variables within the same quarter. We thus order it last in the vector of endogenous variables. The model is estimated over 1990:Q4-2013Q4 using one lag of the endogenous variables, a lag length consistent with the Bayesian information criterion (BIC).[27]

Figure 3 shows the responses of the endogenous macroeconomic variables to a negative shock on the aggregate bank capital buffer. The bank capital shock is calibrated to -100 basis points, which roughly matches the observed decrease in the ABCB from 2007Q3 to 2008Q3. The 95% confidence intervals are constructed following Kilian (1998) using a bootstrap with 5000 replications. The credit spread increases on impact by almost 60 basis points and remains significantly positive during 5 quarters. This confirms that the negative bank capital shock translates into a negative credit shock. A reason why this would occur is that the negative capital shock reduces the risk-bearing capacity of large banking institutions thus leading them to require higher credit risk premia (see for instance Gilchrist and Zakrajsek, 2012). The growth rate of C&I loans does not react on impact, consistently with the intuition that contractual constraints limit the adjustment, but it then steadily declines with a maximum response of about -6% after one year. GDP growth drops significantly during the first year after the shock with a maximal response of -1.3% after six months. Consequently, the federal funds rate is lowered during the same period and monetary policy remains accomodative for about two years, although the response of CPI inflation is not significant.

Furthermore, Table 6 provides the forecast variance decomposition of a shock to the aggregate bank capital buffer. The second column presents the results in the baseline case, while the other columns refer to alternative specifications that we will comment on below in the robustness section. Our measure of the bank capital shock explains a non-negligible share of the fluctuations in the endogenous variables. At the horizon of one year, the bank capital shock accounts for some 4% of the variance of GDP growth, 11% of the variance of C&I loan growth, and 10% of the variance of the corporate credit spread. These results are in line with the available evidence of the importance of credit shocks for macroeconomic fluctuations (see Boivin et al., 2013; Gilchrist et al., 2009; Meeks, 2012). The effect is however 4 to 5 times lower than

[27]Our results remain valid if we use more lags in the VAR, see below.

what Bassett et al. (2014) find in response to a shock to bank lending standards. A possible reason for this discrepancy can be that unwanted changes to the capital buffer of large banks only account for a limited share of fluctuations in banks' credit supply standards, as other constraints (like liquidity and funding constraints, competition, shocks to the perceived credit risk of new borrowers etc.) are also likely to affect them.

C. Robustness

We check in this section that the results presented above are robust to a series of changes to our baseline model specifications: we therefore look in turn at alternative identification schemes, alternative choices of the number of lags of endogenous variables in the VAR, alternative measures of the ABCB and alternative measures of real activity.

First, the recursive ordering chosen for the benchmark model may seem overly restrictive. In particular, it implies that the federal funds rate is constrained not to respond to an ABCB shock within the same quarter. Indeed, FOMC meetings take place almost every six weeks, and even more frequently during the recent crisis, which makes it possible that the Fed reacts within a quarter to bad news regarding the capital position of major BHCs. We therefore compare the IRFs obtained with the benchmark model to two alternatives where we implement two different ordering schemes. Under "Ordering 1", the ABCB is placed before the Fed funds rate, so that monetary policy can freely react to a shock on bank capital. "Ordering 2" corresponds to the case where the ABCB is ordered after both the Fed funds rate and bank loan growth, which implies that the response of bank C&I loans is also restricted not to react on impact to a bank capital shock. Figure 4 shows the IRFs to a 100 bp bank capital shock under each of these alternative ordering schemes. The figure confirms that the results obtained for the baseline ordering are qualitatively robust to these changes.

In the benchmark model, the lag order of one has been estimated by the BIC, which is not surprising given the small length of our time series. However, we verify the robustness of our results to richer lag structures by conditioning on the 2 or 3 previous quarters.[28] The size of the impulse responses is smaller for some variables, and some are also more volatile, as is usual when the number of lags in the VAR increases. Qualitatively however, the pattern of the responses to the ABCB shock seems robust.

We also run the same analysis while using alternative measures of the aggregate bank capital buffer. The first of these alternative measures is $ABCB_t^{het}$, which we constructed from the "heterogenous" panel model as explained above. Associated impulses responses are presented in Figure 5. The second and third measures are the unweighted average and the median of individual bank capital buffers, respectively.[29] Qualitatively, the results are similar to the baseline case. Interestingly however, allowing for more heterogeneity across banks when estimating the leverage targeting model yields an aggregate measure of the bank capital buffer that explains a larger share of the variance of macroeconomic variables, as shown in column 3 of Table 6. The

[28]See the corresponding figures in Appendix B.
[29]See Appendix B for more details.

bank capital shock now explains more than 6% of the variation in GDP growth at a one-year horizon, and some 21% of the variation in C&I credit growth and the BAA credit spread. In contrast, shocks to the unweighted average or the median of bank-level capital buffers produce much smaller macroeconomic effects than in the benchmark case, explaining e.g. less than 2% of the variance of GDP at a one-year horizon. This last result confirms that the size distribution of financial institutions matters for the macroeconomic consequences of bank capital shocks, in line with the findings of other studies on the "granularity" of credit developments in major economies (Buch and Neugebauer, 2011; Bremus et al., 2013).

In addition, we also considered other real activity measures instead of GDP: the unemployment rate (UR), investment (INV) and industrial production (INDPRO). The recursive ordering remains the same as in the benchmark model, with the real activity variable coming first.Our findings are robust to this change in the measure of real activity.[30] For instance, the impact of the capital buffer shock on unemployment is sizable, with a peak reached after six quarters. As shown in Table 6 (columns 7 and 8), the aggregate bank capital shock accounts for 15% of the variance of unemployment after one year and for 12% of the variance of corporate investment.

IV. Conclusion

We proposed in this paper a new simple approach which draws on both micro and macro data and models in order to quantify the macroeconomic consequences of shocks to the leverage ratio of large banks. Our methodology combines a standard empirical microeconometric model of bank leverage targeting with a standard dynamic model of the macroeconomy. We applied this methodology to the US economy over the last 25 years. We first constructed a new aggregate measure of the capital buffer of large US banking institutions, i.e., the difference between their actual and their desired unweighted capital ratios, which proves to be quite volatile and strongly correlated with usual proxies of aggregate credit constraints. We then plugged it into a structural VAR model of the US economy, which allows us to account for the dynamic interactions between capital constraints in the banking system and the macroeconomy. We find that shocks to the capital buffer of large banking institutions in the US explain a substantial share of the variance of bank credit to firms, the corporate credit spread and real activity. When the aggregate capital buffer of large bank holding companies is unexpectedly squeezed, this triggers a surge in credit spreads, a sharp contraction of bank credit and a slowdown of activity, which is however progressively dampened by the more accommodative stance of monetary policy.

In the context of our study, the regulatory constraint on bank leverage is slack, so that the desired capital ratio targeted by an individual institution is an "economic" capital ratio, which is driven by market forces and fluctuates widely. This situation may change with the progressive implementation up to 2018 of the new Basel III regulation on bank leverage. Our findings suggest that a surprise and rapid implementation of heightened regulatory constraints on bank leverage could have significantly contractionary effects in the short run. However, the new Basel

[30]The IRFs for the model variants with UR, INV and INDPRO instead of GDP are shown in Appendix B.

regulations did not catch the industry by surprise as they have first been thoroughly discussed with banks and are being very progressively implemented over a period of several years. In steady-state, to the extent that a leverage regulation is tough enough, the constant regulatory leverage ratio may become binding, while the time-varying economic one may not bind anymore. As a consequence, one may expect fluctuations in the aggregate bank capital buffer of large banks to be dampened. The role of the banking system in amplifying macroeconomic fluctuations should diminish accordingly.

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TABLE 1. Summary statistics for bank-level variables used in the econometric model of bank capital

	Nb.	mean	p50	sd	p10	p90
Assets (USD mns)	6,107	105,575	22,199	288,742	6,385	211,741
Capital/A.	6,107	9.00	8.25	5.95	6.03	11.48
ROA	6,107	2.81	2.47	3.87	0.63	5.25
Loans/A.	6,107	59.50	64.15	16.30	37.07	74.55
Mortg. Loans/A.	6,107	29.55	29.58	14.78	9.35	48.13
C&I Loans/A.	6,107	14.32	13.92	8.21	4.82	23.81
Net Chargeoffs/A.	6,107	1.11	0.60	1.59	0.07	2.68

Note. All variables are expressed in percentage points, unless otherwise stated.

TABLE 2. Summary statistics for macro variables used in the econometric model of bank capital

	N	mean	p50	sd	p10	p90
Forec. GDP growth	112	2.64	2.67	0.59	2.01	3.33
Forec. Δ short rate	112	0.32	0.25	0.46	-0.12	1.00
GDP growth	112	2.61	2.87	1.77	0.64	4.35
BAA spread	112	2.85	2.64	1.08	1.71	4.21
S&P500 Volat.	112	1.01	0.83	0.59	0.56	1.55

Note. *Forecasted GDP growth* is the one-year-ahead forecast of GDP growth. *Forecasted Δ short rate* is the expected variation over the next year of the 3-month TBill rate. *GDP growth* is the year-on-year growth rate of real GDP (in logs). All three series are constructed using real-time vintages of the Philadelphia Fed's Survey of Professional Forecasters. *BAA spread* is the spread between Moody's BAA corporate yield and the yield of the 10-year Treasury bond. *S&P500 Volat.* is the realized volatility of the daily S&P index return over one quarter. All variables are expressed in percentage points.

TABLE 3. Summary statistics for macro variables in SVARs

	N	mean	median	sd	p10	p90
GDP Growth (GDP)	93	2.42	2.74	2.56	-0.57	5.09
Unemployment Rate (UR)	93	6.11	5.67	1.63	4.38	9.01
Real investment growth(INV)	93	4.10	4.87	13.05	-9.14	17.62
Industrial Production growth (INDPRO)	93	2.03	2.98	5.28	-5.50	6.98
CPI Inflation (CPI)	93	2.56	2.84	1.98	0.90	4.28
Federal Funds Rate (FFR)	93	3.42	3.77	2.31	0.15	5.82
C&I Loans growth (LOANS)	93	3.82	7.39	9.77	-7.69	13.91
BAA Corporate credit spread (CREDIT SPREAD)	93	2.35	2.15	0.80	1.56	3.20
ABCB (CAPITAL BUFFER)	93	-0.59	-0.53	0.71	-1.46	0.23

Note. Growth rates are quarter-on-quarter growth rates (in logs), expressed in annual terms. All variables are expressed in percentage points.

TABLE 4. Determinants of BHC capital-to-asset ratios

	All banks		Banks sorted by average size			
			$. > p75$	$p75 > . > p50$	$p50 > . > p25$	$. < p25$
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Capital/A.	0.926***	0.922***	0.935***	0.911***	0.925***	0.915***
	(0.009)	(0.010)	(0.012)	(0.021)	(0.027)	(0.011)
Size	0.100***	0.102***	0.031*	0.141***	0.094	0.120*
	(0.021)	(0.022)	(0.017)	(0.038)	(0.055)	(0.063)
ROA	-0.002	0.001	-0.003	0.001	-0.018**	0.002
	(0.005)	(0.005)	(0.010)	(0.007)	(0.007)	(0.007)
Net Chargeoffs/A.	0.018	0.010	0.005	0.024	0.002	-0.005
	(0.012)	(0.013)	(0.017)	(0.029)	(0.034)	(0.018)
Mortg. Loans/A.	-0.003**	-0.004**	-0.003	-0.005**	0.001	-0.004*
	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)
C&I Loans/A.	-0.000	0.002	0.000	-0.003	0.009*	0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)
Forec. GDP growth		-0.045**	-0.031	-0.026	-0.061	-0.060
		(0.021)	(0.029)	(0.048)	(0.041)	(0.044)
Forec. Δ short rate		0.026	0.013	0.042	0.034	0.003
		(0.018)	(0.023)	(0.038)	(0.046)	(0.033)
GDP growth		0.001	-0.004	-0.005	0.010	0.009
		(0.007)	(0.008)	(0.011)	(0.011)	(0.023)
BAA spread		0.040***	0.052***	0.062***	0.049	0.014
		(0.015)	(0.015)	(0.021)	(0.030)	(0.038)
S&P500 Volat.		-0.082***	-0.039	-0.067	-0.199***	-0.019
		(0.024)	(0.032)	(0.045)	(0.053)	(0.054)
Observations	5616	5616	1413	1425	1370	1408
Adjusted R^2	0.874	0.875	0.910	0.908	0.865	0.832

Note. This table presents fixed effect panel regressions where the dependent variable is the banks' capital-to-asset ratio. All explanatory variables are lagged by one quarter. *Size* is the log of total assets in USD thousands. *S&P500 Volat.* is the log of the realized volatility of the daily S&P500 index return over a quarter. A constant and quarterly seasonal dummies are included but not shown. Columns (1-2) present results for all selected banks, while columns (3-6) present results for different quartiles of the bank population where banks are sorted according to their average share of total banking assets. Standard errors are clustered at the bank-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 5. Pairwise Granger causality testing results

y=.	H_0: ABCB $\nrightarrow$ y	H_0: y $\nrightarrow$ ABCB	AIC lags
AAA Credit Spread	0.6	0.06	3
BAA Credit Spread	0.41	0.02	3
SLOOS Loan Spreads (Large firms)	0.03	0.01	4
SLOOS Loan Spreads (Small firms)	0.06	0.02	3
SLOOS Lending Standards (Large firms)	0.07	0.04	4
SLOOS Lending Standards (Small firms)	0.04	0.04	4
% Loans under Commitment	0.05	0.08	2

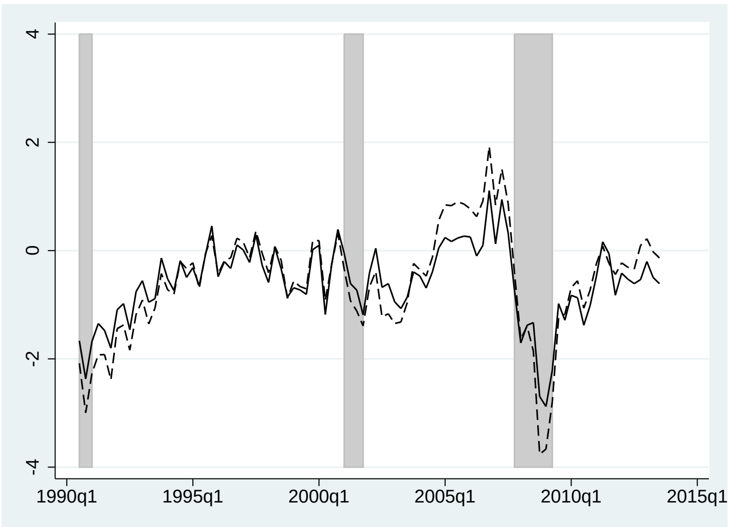
Note. This table presents Granger causality pairwise testing. The second column contains p-values of the null hypothesis that capital buffer does not Granger cause the left row variable, while the third column tests whether the row variables Granger cause the capital buffer measure. The final column shows the AIC estimate of each bivariate VAR lag order.

TABLE 6. SVAR evidence: variance decomposition

	horizons	Benchmark	Heterogenous	Average	Median	UR	INV	IND
GDP	h=2	0.0391	0.0582	0.0052	0.0118	0.1063	0.1217	0.0449
	h=4	0.0401	0.0625	0.0118	0.0151	0.1514	0.1219	0.0478
	h=12	0.0401	0.0625	0.0120	0.0152	0.1452	0.1217	0.0477
CPI	h=2	0.0006	0.0035	0.0058	0.0093	0.0013	0.0017	0.0009
	h=4	0.0011	0.0060	0.0066	0.0099	0.0020	0.0023	0.0015
	h=12	0.0011	0.0060	0.0067	0.0099	0.0020	0.0023	0.0015
FFR	h=2	0.0247	0.0409	0.0017	0.0009	0.0327	0.0470	0.0188
	h=4	0.0563	0.1240	0.0049	0.0027	0.0729	0.0975	0.0449
	h=12	0.0530	0.1200	0.0168	0.0108	0.0690	0.0923	0.0422
CB	h=2	0.7310	0.7113	0.7449	0.7240	0.7266	0.8250	0.7161
	h=4	0.7052	0.7033	0.7231	0.6991	0.6956	0.8002	0.6900
	h=12	0.7043	0.7014	0.7220	0.6977	0.6951	0.7993	0.6891
LOANS	h=2	0.0763	0.1119	0.0840	0.0677	0.0887	0.1115	0.0653
	h=4	0.1061	0.2115	0.0816	0.0678	0.1295	0.1535	0.0905
	h=12	0.1078	0.2148	0.0815	0.0679	0.1323	0.1560	0.0921
CS	h=2	0.1054	0.2202	0.0485	0.0556	0.1300	0.1615	0.0770
	h=4	0.0936	0.2109	0.0575	0.0555	0.1189	0.1437	0.0682
	h=12	0.0931	0.2097	0.0578	0.0556	0.1183	0.1430	0.0678

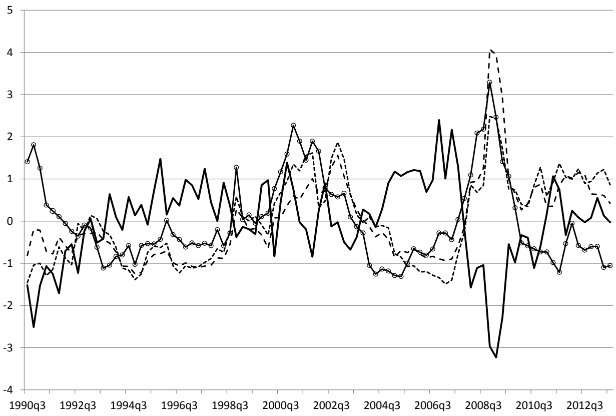
Note. This table presents the share of the variance of macro variables explained by a negative shock on the ABCB at the horizons of 2, 4 and 12 quarters. *Heterogenous* corresponds to the measure of the aggregate bank capital buffer constructed from the heterogenous panel. *Average* and *Median* stand for models using as a measure of the ABCB the simple unweighted average and median capital buffer over selected banks. The last three columns stand for VAR models where the real activity variable is either the rate of unemployment (UR), Investment (INV) or Industrial production (IND) instead of GDP growth.

FIGURE 1. The estimated Aggregate Bank Capital Buffer (ABCB)



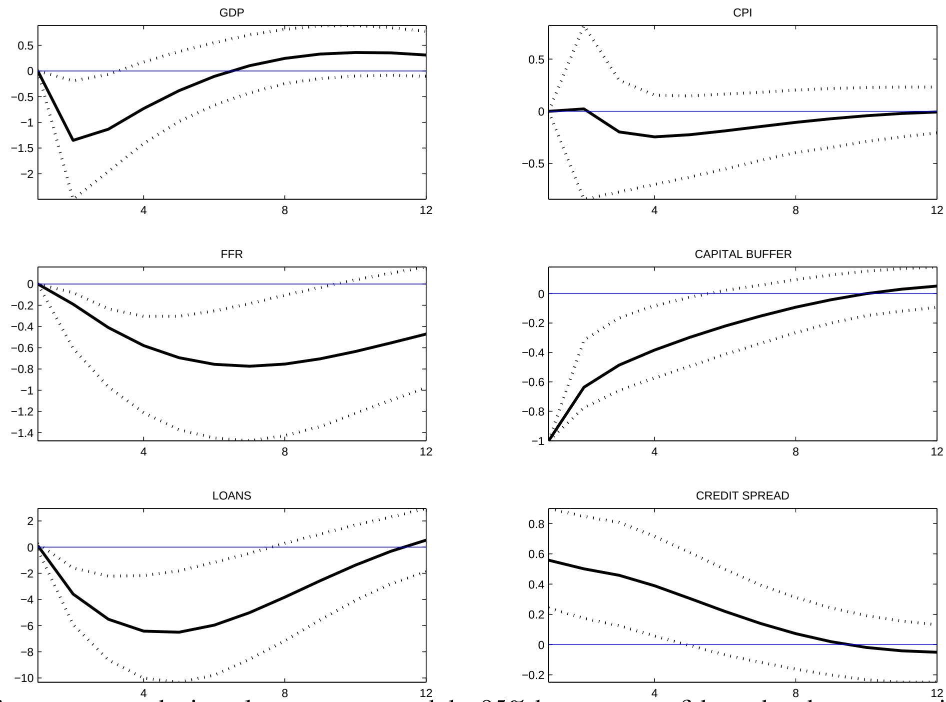
Note. Baseline estimate (solid) and alternative estimate allowing for heterogenous coefficients across BHCS belonging to for different size buckets (dashed). Shaded areas delimit NBER recessions.

FIGURE 2. Aggregate Bank Capital Buffer, corporate credit spreads and SLOOS index of credit conditions



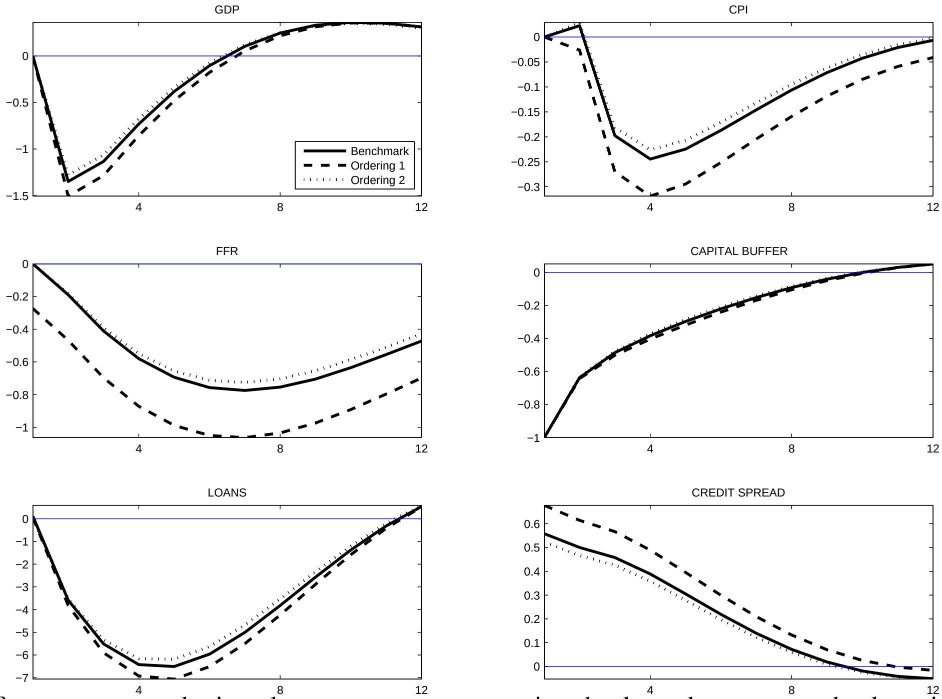
Note. Baseline estimate of the ABCB (solid line), spreads of AAA (dotted line) and BAA (dashed line) corporate bond yields from Moody's against 10 year Treasuries (AAACS and BAACS, respectively) and Net Percentage of Domestic Respondents Tightening Standards for Commercial and Industrial Loans to Large and Medium Firms from the Fed's SLOOS (solid line with circles). All variables are demeaned and standardized for comparison purpose.

FIGURE 3. Responses of macro variables to an ABCB shock: the benchmark model



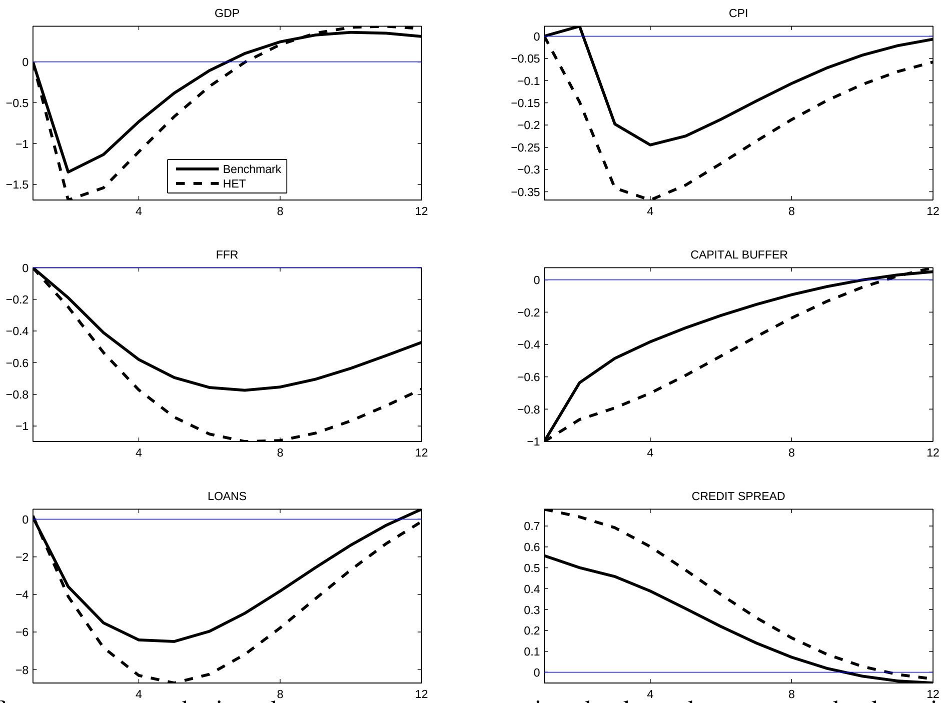
Note. This figure presents the impulse responses, and the 95% bootstrap confidence bands, to a negative shock on the aggregate bank capital buffer of one percentage point.

FIGURE 4. Responses of macro variables to an ABCB shock: robustness to ordering



Note. This figure compares the impulse responses, to a negative shock on the aggregate bank capital buffer of one percentage point, of the benchmark model with the results obtained from SVARs identified under Ordering 1 [GDP, CPI, CB, FFR, LOANS, CS] and under Ordering 2 [GDP, CPI, FFR, LOANS, CB, CS].

FIGURE 5. Responses of macro variables to an ABCB shock: heterogenous panel



Note. This figure compares the impulse responses, to a negative shock on the aggregate bank capital buffer of one percentage point, of the benchmark model to the same specification but with the ABCB constructed from the heterogenous panel model.

Appendix A. Data (Not for publication, online appendix)

A. *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)

B. *List of BHCs in selected sample*

BHC id	BHC Name	Total assets	Equity to Assets	Nb. Obs.	Share of total
1074660	ALLFIRST FINANCIAL INC.			53	
1078604	AMSOUTH BANCORPORATION			67	
1199769	BANA HOLDING CORPORATION			71	
1028739	BANC ONE ARIZONA CORPORATION			32	
1200432	BANC ONE INDIANA CORPORATION			35	
1096185	BANC ONE KENTUCKY CORPORATION			32	
1250932	BANC ONE OHIO CORPORATION			32	
1473562	BANC ONE TEXAS CORPORATION			43	
1025608	BANCWEST CORPORATION	83527474	14.20023	96	.5444309
1073757	BANK OF AMERICA CORPORATION	2.105e+09	11.05395	96	13.72033
1025309	BANK OF HAWAII CORPORATION	14127598	7.163115	96	.0920835
1033470	BANK OF NEW YORK COMPANY, INC., THE			70	
1068294	BANK ONE CORPORATION			58	
1026016	BANKAMERICA CORPORATION			34	
1112076	BANKBOSTON CORPORATION			39	
1076776	BARNETT BANKS, INC.			32	
1074156	BBANDT CORPORATION	1.830e+08	12.43582	96	1.192857
2947435	BBVAPR HOLDING CORPORATION			48	
1020340	BMO BANKCORP, INC.			87	
1245415	BMO FINANCIAL CORP.	1.111e+08	12.52022	96	.723977
2277860	CAPITAL ONE FINANCIAL CORPORATION	2.973e+08	14.04208	37	1.93768
1026632	CHARLES SCHWAB CORPORATION, THE	1.436e+08	7.226995	38	.9362565
1042351	CITICORP			62	
1023314	CITICORP HOLDINGS, INC.			39	
1951350	CITIGROUP INC.	1.880e+09	10.86689	61	12.2563
1199844	COMERICA INCORPORATED	65356580	10.94351	96	.4259933
1049341	COMMERCE BANCSHARES, INC.	23081892	9.577387	96	.1504474
1116300	CORESTATES FINANCIAL CORP			33	
1072237	CRESTAR FINANCIAL CORPORATION			40	
1102367	CULLEN/FROST BANKERS, INC.	24388272	10.30889	96	.1589624

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BHC id	BHC Name	Total assets	Equity to Assets	Nb. Obs.	Share of total
1079946	DEPOSIT GUARANTY CORP.			33	
2894230	DISCOUNT BANCORP, INC.	9603713	8.271894	56	.0625969
2089036	EMIGRANT BANCORP, INC.			46	
3005332	F.N.B. CORPORATION	13563405	13.08214	51	.0884061
1070345	FIFTH THIRD BANCORP	1.304e+08	11.18391	96	.850224
1078426	FIRST AMERICAN CORPORATION			39	
2744894	FIRST BANCORP	12656925	9.606267	61	.0824977
1199778	FIRST CHICAGO NBD CORPORATION			35	
1075612	FIRST CITIZENS BANCSHARES, INC.	21199091	9.796057	96	.1381754
1033993	FIRST FIDELITY INCORPORATED			32	
1094640	FIRST HORIZON NATIONAL CORPORATION	23791187	9.269483	96	.1550706
1199648	FIRST OF AMERICA BANK CORPORATION			32	
1024058	FIRST SECURITY CORPORATION			54	
1073551	FIRST UNION CORPORATION			75	
1071968	FIRST VIRGINIA BANKS, INC.			54	
1199479	FIRSTAR HOLDINGS CORPORATION			39	
1070804	FIRSTMERIT CORPORATION	23912451	11.30329	96	.155861
1113514	FLEETBOSTON FINANCIAL CORPORATION B*B			57	
1246216	FRANKLIN RESOURCES, INC.	15793167	66.41861	51	.1029396
2081124	GREENPOINT FINANCIAL CORP.			43	
1078921	HIBERNIA CORPORATION			63	
3232316	HSBC NORTH AMERICA HOLDINGS INC.	2.900e+08	10.52929	40	1.890306
1068191	HUNTINGTON BANCSHARES INCORPORATED	59476344	10.25491	96	.387666
2477754	INVESTORS BANCORP, MHC	15605073	5.294605	68	.1017136
1037115	J.P. MORGAN AND CO. INCORPORATED			43	
1039502	JPMORGAN CHASE AND CO.	2.416e+09	8.741937	96	15.74543
1068025	KEYCORP	92991716	11.07972	96	.6061187
1022362	LASALLE NATIONAL CORPORATION			37	
1080371	LOUISIANA BANC ONE CORPORATION			35	
1199497	MANDI LLC			71	
1037003	MANDT BANK CORPORATION	85162391	13.27526	96	.5550873
1871159	MBNA CORPORATION			60	
1068762	MELLON FINANCIAL CORPORATION			70	
1094211	MERCANTILE BANCORPORATION INC.			38	
1072442	MERCANTILE BANKSHARES CORPORATION			68	
2945824	METLIFE, INC.			47	
1199714	MICHIGAN NATIONAL CORPORATION			45	
1069125	NATIONAL CITY CORPORATION			75	
1416774	NATIONSBANK TEXAS BANCORPORATION, INC.			33	
3212091	NEW YORK PRIVATE BANK AND TRUST CORPORATION	6456930	11.95683	41	.0420862
1199611	NORTHERN TRUST CORPORATION	1.029e+08	7.685507	96	.6710092
1199705	OLD KENT FINANCIAL CORPORATION			45	
1246702	PEOPLE'S MUTUAL HOLDINGS			66	
1069778	PNC FINANCIAL SERVICES GROUP, INC., THE	3.206e+08	13.22789	96	2.089642
3133637	PROVIDENT FINANCIAL SERVICES, INC.	7487328	13.49952	44	.0488023
1132449	RBS CITIZENS FINANCIAL GROUP, INC.	1.223e+08	15.70089	96	.7968742
1078332	REGIONS FINANCIAL CORPORATION			58	
3242838	REGIONS FINANCIAL CORPORATION	1.177e+08	13.40109	38	.7669175
1021075	REPUBLIC NEW YORK CORPORATION			39	
1075126	RIGGS NATIONAL CORPORATION			61	
1079441	SOUTHTRUST CORPORATION			59	
1070251	STAR BANC CORPORATION			35	
1111435	STATE STREET CORPORATION	2.430e+08	8.38503	96	1.584054
3152245	STERLING FINANCIAL CORPORATION	10327642	11.7737	34	.0673154

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BHC id	BHC Name	Total assets	Equity to Assets	Nb. Obs.	Share of total
1033872	SUMMIT BANCORP.			44	
1023453	SUNTRUST BANKS OF GEORGIA, INC.			40	
1080148	SUNTRUST BANKS OF TENNESSEE, INC.			40	
1131787	SUNTRUST BANKS, INC.	1.754e+08	12.14689	96	1.143129
2816906	TAUNUS CORPORATION			51	
2389941	TCF FINANCIAL CORPORATION	18402494	10.61252	67	.1199472
1079562	TRUSTMARK CORPORATION	11790383	11.49202	96	.0768496
1119794	U.S. BANCORP	3.640e+08	11.29413	96	2.372684
1049828	UMB FINANCIAL CORPORATION	16911852	8.905382	96	.1102312
1094369	UNION PLANTERS CORPORATION			58	
2467175	UNION PLANTERS HOLDING CORPORATION			32	
1378434	UNIONBANCAL CORPORATION	1.059e+08	13.42326	96	.6902548
2307280	UTRECHT-AMERICA HOLDINGS, INC.	36039452	1.755215	43	.2349046
2801546	W HOLDING COMPANY, INC.			42	
1136157	WACHOVIA CORPORATION			46	
1145476	WEBSTER FINANCIAL CORPORATION	20856659	10.59224	39	.1359434
1027095	WELLS FARGO AND COMPANY			35	
1120754	WELLS FARGO AND COMPANY	1.527e+09	11.14213	96	9.953062
1888193	WILMINGTON TRUST CORPORATION			79	

Note. Total assets, equity to assets ratio and share of total BHC assets are measured as of end 2013 when available at this date.

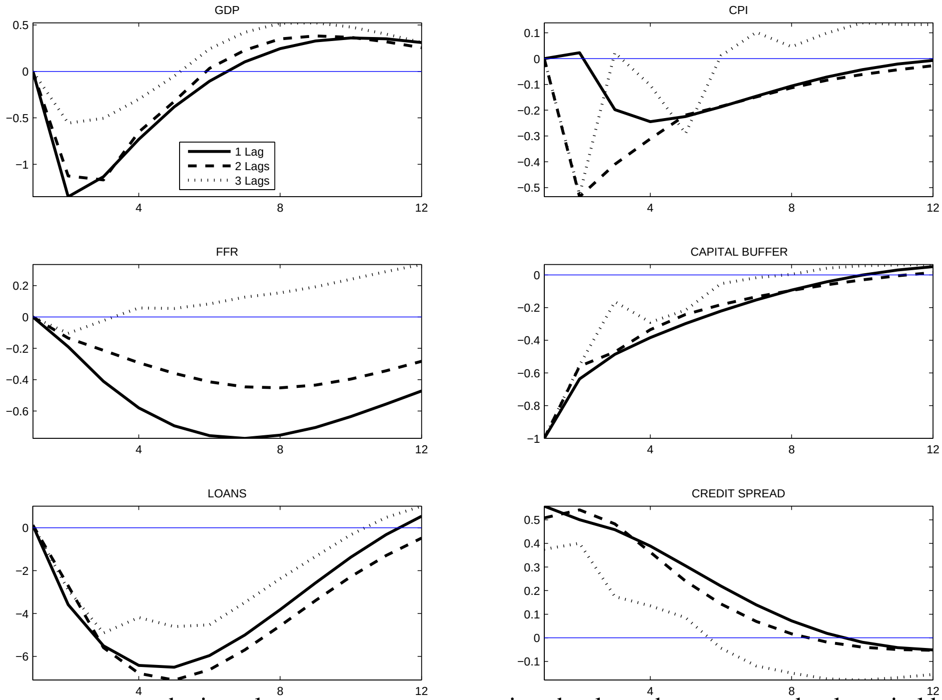
C. Macro data used in the VAR analysis

The transformation codes (TC) are: 1 - no transformation; 2 - first difference; 4 - logarithm; 5 - first difference of logarithm.

TC	Mnemo	Content
5	AHEMAN	Average Hourly Earnings: Manufacturing
5	GDPC1	Real Gross Domestic Product, 1 Decimal
5	GPDI	Gross Private Domestic Investment
5	INDPRO	Industrial Production Index
1	UNRATE	Civilian Unemployment Rate
5	CPIAUCSL	Consumer Price Index for All Urban Consumers: All Items
1	FEDFUNDS	FEDFUNDS, Effective Federal Funds Rate
1	AAA-GS10	Credit Spread AAA
1	BAA-GS10	Credit Spread BAA
5	BK-CIL	Commercial and industrial loans, all commercial banks
Original series used to construct interest rate spread series in the table above		
1	GS10	10-Year Treasury Constant Maturity Rate
1	AAA	BOND YIELD: MOODY'S AAA CORPORATE (% PER ANNUM)
1	BAA	BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM)

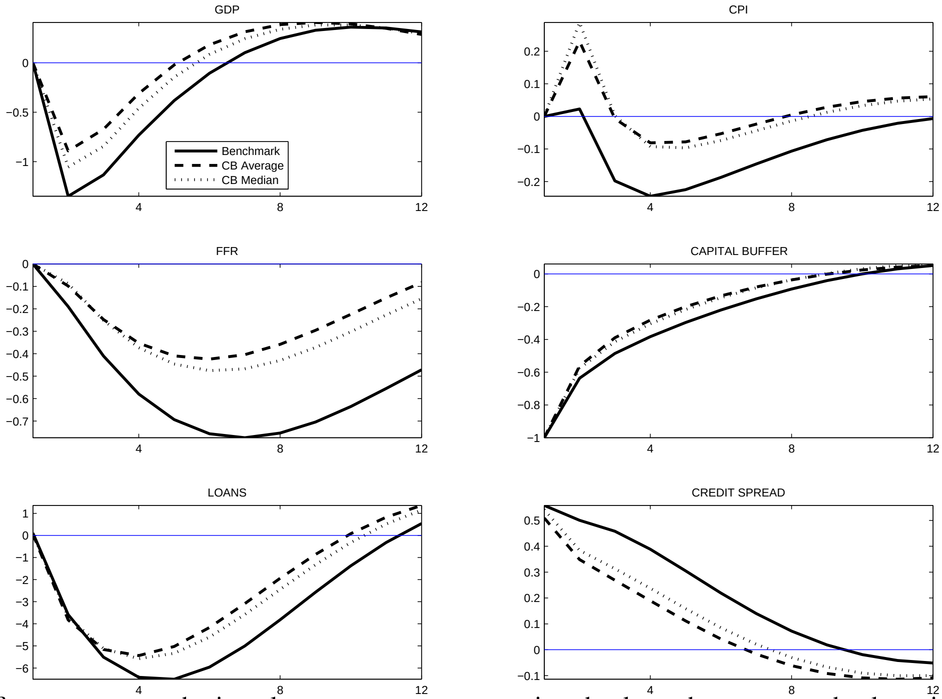
Appendix B. SVAR results: additional robustness checks

FIGURE 6. Responses of macro variables to an ABCB shock: robustness to lag structure



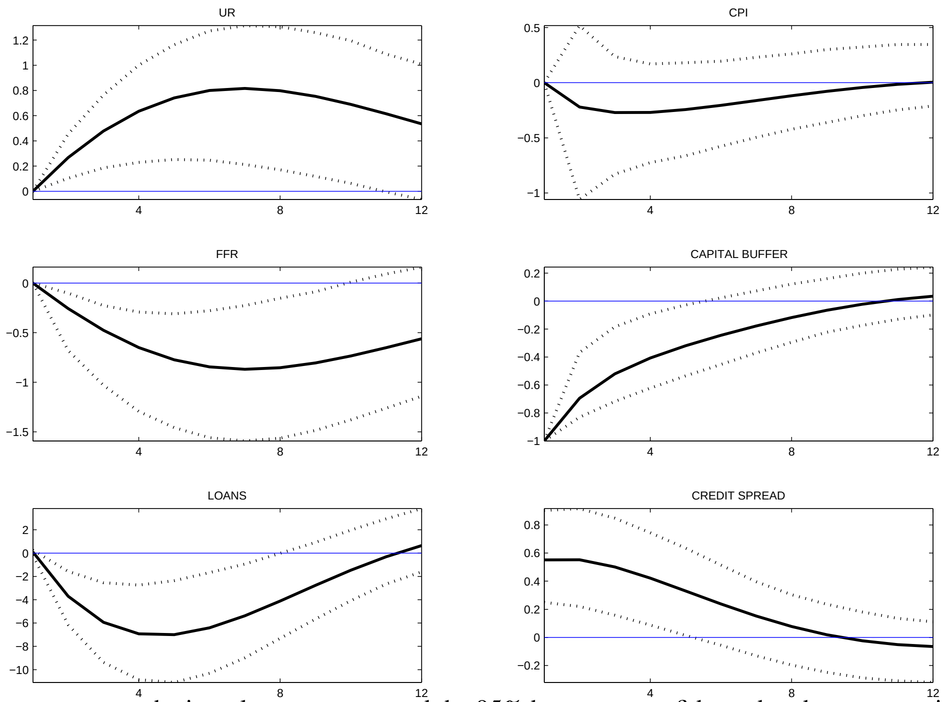
Note. This figure compares the impulse responses, to a negative shock on the aggregate bank capital buffer of one percentage point, of the benchmark model to the responses in SVARs estimated with 2 and 3 lags.

FIGURE 7. Responses of macro variables to an ABCB shock: robustness to unweighted aggregates



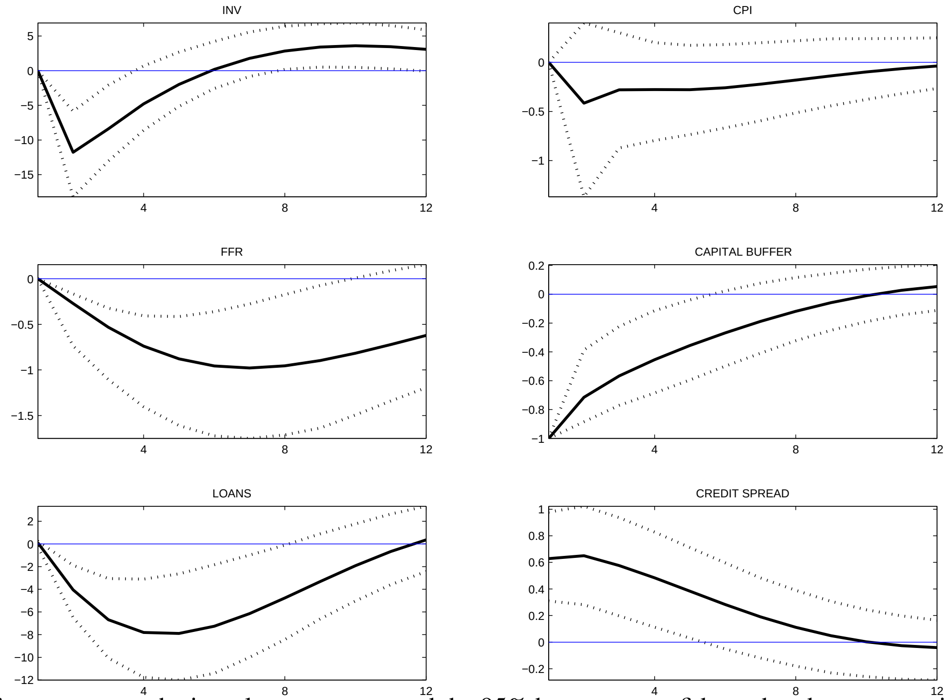
Note. This figure compares the impulse responses, to a negative shock on the aggregate bank capital buffer of one percentage point, of the benchmark model to the same specification but with the aggregate bank capital buffer constructed as the unweighted average and as the median of individual capital buffers.

FIGURE 8. Responses of macro variables to an ABCB shock: robustness to using other real activity measures (unemployment)



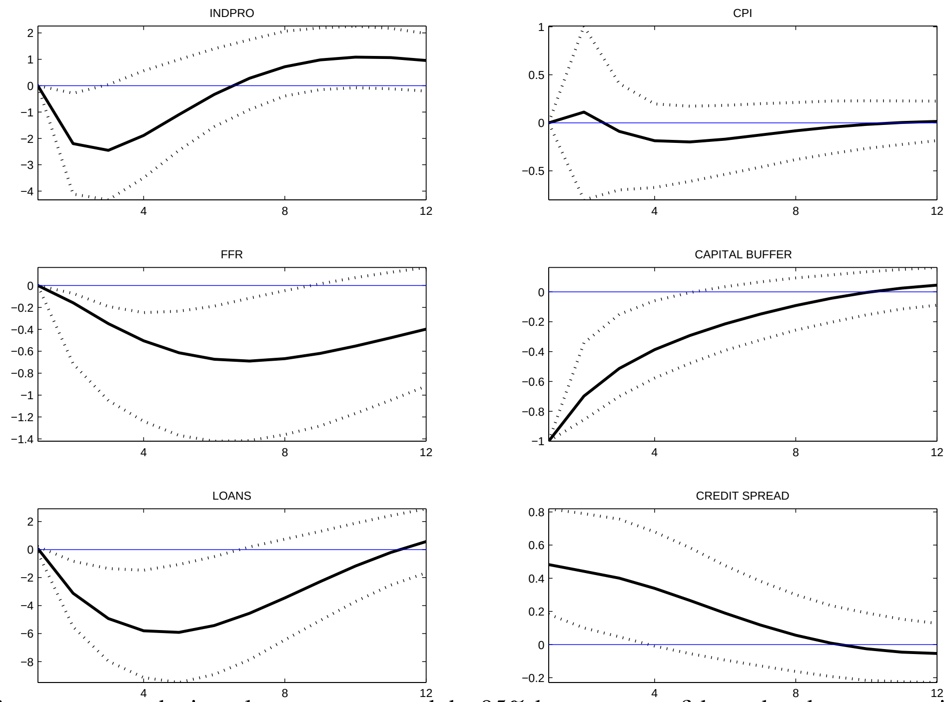
Note. This figure presents the impulse responses, and the 95% bootstrap confidence bands, to a negative shock on the aggregate bank capital buffer of one percentage point.

FIGURE 9. Responses of macro variables to an ABCB shock: robustness to using other real activity measures II (Investment)



Note. This figure presents the impulse responses, and the 95% bootstrap confidence bands, to a negative shock on the aggregate bank capital buffer of one percentage point.

FIGURE 10. Responses of macro variables to an ABCB shock: robustness to using other real activity measures III (Industrial Production)



Note. This figure presents the impulse responses, and the 95% bootstrap confidence bands, to a negative shock on the aggregate bank capital buffer of one percentage point.