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## How do shocks to bank capital affect lending and growth?

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# How do shocks to bank capital affect lending and growth?

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## Abstract

We examine bank capital shocks using a recent new approach based on non-normal errors in vector autoregressive models. Using a sample of 14 European economies over January 2004 through March 2018 we identify two distinct classes of bank capital shocks, capital tightening shocks, and bank profitability shocks. We find that both bank capital shocks frequently lead to changes in lending volume and interest rates for new loans. In contrast to some recent similar studies, we find less evidence for impact on production. Bank capital shocks have further effects on the substitution between the bank and market-based financing and on credit allocation across different borrower sectors. Policymakers may find these results useful when considering counter-cyclical adjustments to the bank capital requirements.

**Keywords:** Structural vector autoregression, Macroprudential policy, Bank capital, Bank profitability, Bank lending

**JEL Classification:** C11, C32, C54

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## 1. Introduction

Since the global financial crisis and wide-spread adoption of the Basel III regulatory standards, central banks and other public authorities have taken a more active role in steering the financial stability. To date, the number of *new* prudential instruments is so vast that, in the public eye, the prudential policy is rising to a stature similar to that of monetary policy. One class of prudential instruments is based on adjusting banks' capital requirements – crudely speaking the amount of shareholder's equity banks need to hold relative to their risk-adjusted asset base. The various capital requirements target either bank-specific micro risks or broader macro risks. To demonstrate the scope of macroprudential activities in Europe, between 2014 and June 2018 the European Systemic Risk Board received more than 500 notifications related to capital requirements and 140 notifications related to other macroprudential measures from the national authorities, altogether averaging to 5 decisions per country per year.<sup>1</sup> During the ten years from January 2008 to January 2018, euro area MFIs increased their capital by 0.87 trillion euros corresponding to increase of capital-to-asset ratio (*capital ratio*) from 5.7 % to 8.3 % (see Figure 1).

Here, our primary objective is to improve on the earlier vector autoregression (VAR) based empirical studies (eg., Lown and Morgan 2006; Berrospide and Edge 2010; Mésonnier and Stevanovic 2017; Kanngiesser et al. 2017; and Noss and Toffano 2014) that aim to quantify the macro effects of bank capital shocks. New findings result from a broad dataset and a novel identification scheme (Lanne et al. 2017; Lanne and Luoto 2016) that provides a unique identification as long as the error terms are not normally distributed.

A key point regarding the empirical literature is that there is a large variation in outcomes and the results seem to depend on location and time period. Moreover, there are serious concerns regarding the identification because of endogeneity and credit supply-demand effects as highlighted in the useful commentary by Peydró (2010). Also a more general criticism applies to traditional shock identification methods. To tackle the first issue, we utilize a relatively extensive monthly dataset that covers 13 + 1 European countries and about 15 years for each country (2004m1–2018m3).<sup>2</sup> However, the paper's main contribution is to the identification puzzle and comes in several forms:

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<sup>1</sup> Measures related to capital requirements: Capital conservation buffer (29), countercyclical capital buffer (333), G-SII buffer (23), O-SII buffer (95), Systemic Risk Buffer (30), Risk Weights (18), Pillar II (6), Leverage ratio (2). We do not include the 81 reported reciprocity measures. Other measures include e.g., Borrower based instruments (LTV/DTI/DSTI/...) (48), Liquidity ratio (11), Loan amortization (9), Loan maturity (9), Stress test requirements (11). [https://www.esrb.europa.eu/national\\_policy/html/index.en.html](https://www.esrb.europa.eu/national_policy/html/index.en.html)

<sup>2</sup> The 13 countries are Germany, France, Great Britain, Italy, Spain, Finland, Sweden, Denmark, Austria, Belgium, Netherlands, Portugal, Ireland, and the '+1' is Euro area aggregate.

- (1) Bank capital is endogenous to economic and financial conditions, so the general equilibrium effects are perhaps best captured by a VAR approach. We include endogenous control variables both for the business cycle conditions *and* financial conditions (financial uncertainty and credit quality).
- (2) It is often difficult to disentangle the credit supply and credit demand effects since changes in the two are correlated. For example, during a downturn, the lending standards may tighten as the business environment and firm profitability deteriorates and loan demand from corporations decline due to increased uncertainty regarding investment needs and profitability. To the extent that the endogenous controls do not capture the full credit demand effect, we need a way to identify credit supply and credit demand shocks (or at least credit supply shocks and aggregate demand shocks) or risk having biased estimates. To the extent that the credit supply and demand are both relevant shocks and are not perfectly correlated, it should be possible to identify the two shocks simultaneously with our methodology.<sup>3</sup>
- (3) Lending substitution effects may be subtle and time-dependent. Although substitution between lender banks (in the same country) should not be a problem when we use aggregate banking sector data, substitution from corporate to household borrowers (Kanngiesser et al. 2017) and from bank lending to security issuance (Noss and Toffano 2014) are potentially significant issues. To capture such effects, we consider alternative specifications that allow for such substitution effects.
- (4) Finally, traditional shock identification procedures such as Cholesky decomposition are dependent on the ordering of the variables, which may lack a reasonable basis. A more recent innovation is to use economically founded sign-restrictions for shock identification. However, this has two major drawbacks: the impulse responses are not uniquely identified, but set-identified. This amounts to a multiple models problem so that many models provide the same fit to data, but their impulse responses can look quite different (see Fry and Pagan 2011).<sup>4</sup> Besides, imposing the sign-restrictions amounts to setting possibly too strong subjective prior distributions for the parameters, which may be in disparity with the actual data (see Baumeister and Hamilton 2015).

Our contribution is to apply the novel method (Lanne et al. 2017; Lanne and Luoto 2016) to the identification of bank capital shocks in Structural Vector Autoregressive (S-VAR) model. Using the full statistical properties of the shock process allows us to identify the relevant shocks directly from the data, given that the shocks are indeed non-normal. Usually in the S-VAR literature the error terms are assumed to be jointly normally distributed. As the reduced form error term distribution is determined by co-variances only, the structural errors cannot be identified without additional restrictions.

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<sup>3</sup> Because we are primarily interested in credit supply shocks, it is not necessary to strictly distinguish between aggregate demand and credit demand shocks, which could be difficult.

<sup>4</sup> Fry and Pagan (2011) highlight that the set-identified distribution of impulse response values *across models* is entirely different from distributions related to sampling uncertainty that arise from Bayesian or bootstrap approaches.

Our application covers a large number of European economies. We carefully take into account the identification issues that relate to bank capital shocks and use Peydró (2010) as a guide. We find interesting new evidence on the impact of bank capital shocks to lending, spreads, and production as well as on the lending substitution effects of the capital shocks. The results should be useful, e.g. for national authorities who decide on capital regulation and macroprudential instruments such as the countercyclical capital buffer.

We structure our analysis into three parts. In the first part (Section 4.1), we tackle identification issues 1, 2, and 4. We estimate a basic model that includes bank capital, volume and price of lending, and production. We also estimate an extended model that includes proxies for credit quality and uncertainty. In both cases we find the identification technique justified, in the sense that the error terms' distribution is non-normal. Moreover, we are able to distinguish between credit supply and credit demand shocks based on their signed impact on volume and spread like in Barnett and Thomas (2014). The difference is that we do not impose sign restrictions but observe the signs of the statistically inferred impulse response functions. The credit quality and uncertainty proxies work well and make the identification more robust. Before proceeding to the main results, we test our model with US data. Intuition would suggest that lending standards should guide the developments in lending and we want to check if our model can identify shocks that support this intuition. The credit supply shock that we obtain is similar to the one that is found by Lown and Morgan (2006).

The second part (Section 4.2) examines the basic properties of bank capital shocks. We establish, by country, the number of distinct economic shocks that have marked impact on bank capital. An interesting finding is that there is often more than one relevant shock. We classify these shocks into *capital tightening* and *bank profitability shocks* according to their signed impact on variables. A capital tightening shock has a positive impact on bank capital and (possibly) negative impact on credit supply. A bank profitability shock has a negative impact on bank capital and (possibly) negative impact on credit supply. Then we investigate if our bank capital shocks are similar to those found in the earlier VAR literature, specifically if they have the instantaneous impact on lending, spreads, and production assumed by Kanngiesser et al. (2017) and others. This is done by calculating the impulse response functions for the statistically identified shocks and counting the share of posterior draws that satisfy the sign relations. We find some evidence in favor of such shocks. However, bank capital shocks that affect only lending volume or spread appear much more likely. Hence we find less evidence than Kanngieser et al. (2017) that capital shocks would have an immediate impact on real variables. Moreover, we find that bank profitability shocks are empirically more likely to have real effects than capital tightening shocks. This can be explained by an unwillingness to knowingly increase bank capital when it would cause harm to the economy. Finally, we find that the shocks' impact is often not instantaneous, but more gradual.

The third part (Section 4.3) introduces relative lending measures to capture the substitution effects, the remaining point on our identification checklist.<sup>5</sup> We find evidence both for substitution of lending to households from firms and from bank lending to market-based finance, as a response to bank capital shocks. Capital tightening shocks have more often a substitution effect on lending volumes than on lending spreads. Profitability shocks tend to have more often immediate impact on the spread than volume. In either case, there is little evidence that the substitution effects would be significant for real economy as the production remains mostly unaffected. The final part (Section 4.4) incorporates robustness checks with inflation and monetary policy rate.

We organize rest of the paper as follows. Section 2 offers a short literature review primarily on the macro effects of bank capital shocks. Section 3 discusses data and the model. Section 4.1 tests the methodology for identifying credit supply and credit demand shocks. Sections 4.2 and 4.3 present the main results of the paper on bank capital shocks related to credit supply effects and substitution effects, respectively. Section 4.4 contains robustness checks and Section 5 concludes with a discussion.

## **2. Related literature**

### ***2.1. Impact on lending and aggregate demand***

Lown and Morgan study the fluctuations in banks' lending standards in explaining commercial bank loans. They study the relationship between credit standards, bank capital and commercial loans in a standard recursive VAR. They find that credit standards are very significant in predicting loan growth and GDP. However, they only note a weak relationship between banks' capital ratios and lending via the lending standards. Berrospide and Edge (2010) study the effect of bank capital on lending with US data on bank holding companies. They also find that bank capital has modest effects on lending and attribute more importance to economic activity and the banks' perception of risks. Interestingly, Berrospide and Edge (2010) find a small positive credit supply effect from positive shock to bank capital while Lown and Morgan (2006) have a small adverse effect. Barnett and Thomas (2014) study credit supply and demand shocks with UK data using an S-VAR model. They identify macroeconomic and monetary policy shocks in addition to credit demand and supply shocks with sign restrictions. They find that credit supply shocks resemble aggregate supply shocks and that they explain movements in spreads and borrowing in the data period that they study. They also estimate that credit supply shocks can explain somewhere between a third to a half of the drop in the GDP relative to the pre-crisis trend.

Financing of consumption and investment is much more dependent on banks in Europe and the monetary union in particular when comparing with the US. European reliance on bank financing invites a conjecture

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<sup>5</sup> Arguably we would get same substitution effects if we introduced multiple sectoral variables in the primary models. The relative lending measures, however, facilitate observing clear signature for the substitution effects without increasing the number of variables.



that banks' capital level and its effect on lending would be much more critical for aggregate production than what it is found in the studies with US data.

Jiménez et al. (2017) study the impact of the Spanish dynamic provisioning policy on credit supply and associated real activities. They find that when the dynamic provisioning was initially implemented, there was virtually no impact on the firms' access to credit as the economic and financial conditions were good. Apart from a slight phase of adjustment firms were able to adjust by borrowing from less affected banks such that impact on credit supply was negligible after three quarters.

The banks' capital level is also important for monetary policy transmission. Ciccarelli et al. (2015) study the monetary policy transmission in the US and Europe with the help of bank lending survey data. They find that the so-called broad credit channel that works through banks' and firms/households balance sheets is important for monetary policy transmission. Our work relates to the traditional bank lending channel that links the supply of credit to changes in monetary policy rates: Change in the policy interest rate affects lenders' external financing premium and thus has an impact on their ability or willingness to lend. The external financing premium is related to the banks' capital adequacy and business model soundness. Inadequate capital may compromise the operation of the bank lending channel as banks are unable to support the economic recovery and transmit monetary easing to firms if their lending capacity is exhausted.

## ***2.2. Sectoral impact of capital shocks***

Kanngiesser et al. (2017) study the impact of bank capital shocks on lending in the euro area households and non-financial corporations. In their sign-restricted S-VAR approach, they describe a bank capital shock as a recessionary shock combined with a capital injection. They find that a capital shock results in a slowdown in lending and increase in the risk premiums for both the household and corporate clients. They also note that the effect on corporate lending is stronger than for mortgage lending which they conclude means that banks respond to the capital shock by adjusting the riskiness of their balance sheet.

The relative amounts of different assets in bank's balance sheet determines its capital position. Assets differ in their perceived/actual riskiness which is displayed by the risk weights that these assets are assigned in the calculation of banks' risk-weighted assets. It is then natural that changes in banks' capital positions or requirements induce banks to change the composition of their assets and hence have an impact on the supply of credit. Daesik and Santomero (1988) study banks' capital regulation in a theoretical framework where banks optimize their asset portfolio depending on the risk weights assigned to different assets. They derive "theoretically correct" risk weights that regulators could use to reach their safety goal.

However, the impact of stricter capital requirements on aggregate credit supply depends also on the elasticity of supply of alternative credit sources. If alternative sources of credit are readily available the changes in capital requirements for banks may not significantly affect the overall credit supply. Consideration of these

effects is of paramount importance for macroprudential policymakers who predominantly have tools to affect banks capital requirements.

Aiyar, Calomiris, and Wieladek (2014 ab) study the impact of changes in banks' capital ratios on credit supply in the UK. They focus in particular on leakages whereby credit supply is shifted from banks that are subject to tighter capital requirements to foreign subsidiaries, foreign-regulated branches or capital markets. They find substantial evidence on leakages in their panel regressions regarding branches of foreign banks operating in the UK. However, they do not find very significant leakages via securities issuance. Noss and Toffano (2016) study the effects of increasing aggregate bank capital with the UK data. They find that tighter capital requirements result in reduced lending that has a more pronounced effect on corporate lending than on household lending. In contrast to Barnett and Thomas (2014) and they do not find strong evidence that capital requirements would affect GDP growth. Uluc and Wieladek (2017) study the impact of changes of banks capital requirements on mortgage loan supply with loan-level data from UK banks and building societies. They find that rise in banks capital requirements results in a decline in loan size and they also find evidence of risk shifting where banks increase their lending to comparatively riskier clients. On the other hand, locally competing lenders expand their lending by an offsetting amount and the contraction in bank lending does not necessarily result in a decrease of credit offered. They find no evidence of credit substitution from non-bank companies. Acharya et al. (2017) study the transmission of macroprudential policies with Irish data. They find that most affected banks increase their corporate lending more than other banks and that banks increase their holding of risky securities. Jiménez et al. (2017) study also the impact of the Spanish dynamic provisioning on the allocation of credit: banks with higher provisioning requirements focus more on firms with higher interest and consequently higher probability of default. As firms were able to switch banks during good economic times tighter provisioning requirements had limited effect in dampening the credit boom. Despite the unintended consequence of risk shifting, higher buffers that were built up in the good times mitigated the negative effects of the credit crunch.

### **3. Data and model**

#### **3.1. Variables and data sources**

All our data is sourced from the European Central Bank Statistical Data Warehouse. In contrast to earlier studies that mostly use quarterly data, we use monthly data for the period January 2004 to December 2017.<sup>6</sup> We choose to use monthly data because this gives us more observations on the shock process and proxies for most of the relevant variables are still available on a monthly level. We discuss the variables below while Table 1 provides the ECB series codes and detailed variable definitions.

In choosing the variables we follow the earlier literature (Lown and Morgan 2006, Berrospide and Edge 2010, Kanngiesser et al. 2017, Meeks 2014, Noss and Toffano 2014), which seems to suggest that the most

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<sup>6</sup> Great Britain, Ireland, and Sweden have somewhat shorter data series (cf. Table 2).

important variables to include are a measure bank capital, bank lending, a measure of lending standards or spread, and a measure of real activity.

The banking variables are defined at the national level and include all domestic monetary financial institutions. As a measure of bank capital, we use the capital and reserves divided by total assets of the banking sector.<sup>7</sup> This corresponds to the leverage ratio (or the inverse of leverage) as opposed to risk-weighted capital ratios. In the latter case, the data is at most quarterly and generally short due to the evolving nature of capital regulation.

Similar to Kanngiesser et al. 2017, except that we use national data, we calculate lending growth rates from the index of notional (unadjusted) stocks of corporate and household lending where the counterpart is located in the euro area (e.g. in case of Germany, the German banks' lending to euro area corporations). The index of a notional stock reflects the true loan transactions cleaned from reclassification and revaluation effects. The unadjusted stocks capture the portion of loan stock that remains on the bank balance sheets (i.e., is not securitized and transferred). Because a bank typically has one capital pool for all its lending, we do not restrict to domestic loans but include their total lending to euro area. Finally, we construct the aggregate non-financial sector lending as a sum of corporate and household lending.

In the absence of monthly data on non-price lending standards, we only use price lending standards as measured by lending spreads.<sup>8</sup> Here, the bank lending spreads are also defined in analogy with Kanngiesser et al. 2017. The household lending spread is proxied by the mortgage interest rate for new business less the short rate (short rate is EONIA for Euro area). The corporate lending spread is defined as the corporate loan interest rate less the short rate.

Our primary real sector variables are the industrial production, which serves a similar function as real GDP in other papers. We use the broadest industrial production index from EuroStat that includes construction.<sup>9</sup> Many papers prefer to include policy interest rate and inflation to link to monetary policy analysis. We keep these two monetary variables outside the core model and only include them in the robustness checks as they are not of primary interest here. The inflation is then measured by the harmonized index of consumer prices (HICP) excluding food and energy. Our short interest rate is the average overnight rate during one month period (EONIA, Libor, or Stibor, depending on country).

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<sup>7</sup> Berrospide and Edge 2010 finds for bank-level data that results are quite similar whether one uses bank capital ratio directly or a capital surplus/deficit derived from capital targeting assumptions.

<sup>8</sup> Berrospide and Edge (2010) incorporate bank lending standards based on the Federal Reserve Board's Senior Loan Officer Opinion Survey. Although the ECB similar has the quarterly Bank Lending Survey (BLS), the data is only available on a quarterly level. The advantage of BLS data is that it also includes lending standards for loans that were never granted as opposed to realized transactions. The advantage of spreads, on the other hand, is that our spread measure is based on full coverage of banks (BLS is based on sample survey) and the spread constitutes a single number, level of which is often more straightforward to interpret than the level of lending standards derived from BLS.

<sup>9</sup> Ireland has only 93 observations because the industrial production series with construction for Ireland ends in September 2011.

Peydró (2010) suggests controlling for borrower quality and demand of credit using firm-bank level data. In the absence of such granular datasets, the best we can do is to use proxy variables for borrower quality and credit demand. Lown and Morgan (2006) experimented with non-performing loans in their study of lending standards. Such data is available only on a quarterly level, so we proxy credit quality with loan losses as captured by the series defined as “other adjustments.” This data series is available within the Eurosystem only internally. Finally, we include a measure known as SovCISS, which integrates credit risk, volatility, and liquidity into an overall measure of uncertainty. Even if plausibly relevant for credit demand, uncertainty to our knowledge has been omitted in the earlier bank capital shock literature.

### 3.2 Descriptive graphics

Figure 1A–L summarizes the development of our set of variables across countries.

Fig. 1A: Past decade has seen a notable increase in the capital ratios and capital requirements of banks. The increases have been in part voluntary but in significant part consequent of tightened regulatory requirements and also capital injections related to crisis management efforts.

Fig. 1B–C: Lending spreads generally widened when the crisis hit Europe. In 2009, the policy rates were also lowered rapidly, which shows up in the calculated spreads.

Fig. 1D–F: Growth in lending generally slowed down or turned negative during the global financial crisis and Euro crisis and remained subdued thereafter.

Fig. 1G: A fast recovery in industrial production initially followed the global financial crisis. The recovery after the Euro crisis has been generally slower.

Fig. 1H: Except for Libor, the short rates entered negative territory late 2014 (Euro Area) or early 2015 (Sweden).

Fig. 1I: Despite the crises, core inflation across countries remained mainly positive during the time period.

Fig. 1J: Market-based finance was volatile compared to bank lending during the period.

Fig. 1K: Loan losses materialized in two waves, with the most significant peak early on during the euro crisis. This pattern is stronger for the corporate loan losses than household loan losses but exists for both.

Fig. 1L: In contrast to industrial production, the median level of systemic stress was the same during the global financial crisis and Euro crisis in this sample. However, there is much more variation across countries during the Euro crisis.

### 3.3 Empirical methodology

We estimate and identify Bayesian SVAR model with non-normal error processes introduced by Lanne and Luoto (2016).<sup>10</sup> The model is

$$y_t = a + \sum_{j=1}^p A_j y_{t-j} + B \varepsilon_t, \quad (3.3.1)$$

where  $a$  is the intercept,  $A_p$  is coefficient matrix at lag  $p$ ,  $B$  is an invertible matrix of contemporaneous structural relations of the error terms  $\varepsilon_t$ . Each component of the error term is assumed to have finite variance and  $E[\varepsilon_{it}\varepsilon_{it'}] = E[\varepsilon_{it}\varepsilon_{jt}] = E[\varepsilon_{it}] = 0$  with  $i \neq j$  and  $t \neq t'$ . If additionally at most one of the error components has a Gaussian marginal distribution, Lanne et al. (2017) show that the matrix  $B$ , and hence the structural shocks, can be identified uniquely apart from permutation and scaling of its columns.

We set the lag length to one as suggested by SBIC and HQIC information criteria. We also experimented with 2 to 4 lags and observed that the impulse response functions look essentially similar.

Following Lanne and Luoto (2016), we assume that each error component follows the  $t$ -distribution with degrees of freedom  $\lambda_i$ .<sup>11</sup> In the Bayesian estimation, we use an exponential prior for the  $t$ -distribution,  $\lambda_i \sim \text{Exp}(\text{mean} = \underline{\lambda}_i)$  with  $\underline{\lambda}_i = 5$ . For the coefficient and structural matrices, we generally use relatively uninformative normal priors.<sup>12</sup>

The posterior distribution is estimated using a Metropolis-within-Gibbs algorithm. The posterior distributions of degrees of freedom parameters are used to check that the error terms indeed are non-normally distributed. See Lanne and Luoto (2016) for details of the estimation procedure. Our estimation uses a code package developed by Nelimarkka (2018), which includes some more optionality and improvement in scalability of the estimation process.

After the estimation, we can calculate the posterior distribution of impulse response functions the usual way

$$\Theta_0 = I, \text{ and } \Theta_i = \sum_{j=1}^i \Theta_{i-j} A_j, \quad i = 1, 2, \dots \quad (3.3.2)$$

where  $A_j = 0$  for  $j > p$ . For  $p=1$  the formula simplifies to

$$\Theta_k = A_1^k B. \quad (3.3.3)$$

Each column of  $\Theta_k$  contains one structural shock. Similar to SVAR literature that uses sign-restrictions, we can interpret the statistically identified shocks based on their impact on a set of variables. Hence, we interpret the shocks based on what is the sign (and magnitude) of impact on different variables. Most of the time we

<sup>10</sup> The model is not available in panel form, so we estimate the model for each country separately.

<sup>11</sup> The  $t$ -distribution is assumed for computational convenience. We expect the results not to be sensitive to the exact form of the assumed distribution as long as the distribution family allows for fatter tails than the normal distribution.

<sup>12</sup> More precisely, we set the variance of the elements of the prior for  $B$  inverse small,  $(V_B^{-1})_{ij} = 10^{-5}$  so that the implicit prior for  $B$  matrix is relatively uninformative. See Lanne and Luoto (2016).

only calculate the probability that a shock satisfies particular economically reasoned sign-relations. For example, an aggregate demand shock would have a positive impact on the production and price level.

The permutation and scaling rule for B-matrix is similar to the one in Lanne and Luoto (2016). With this rule, the  $k$ th shock by definition has a positive impact on the  $k$ th variable. For ease of illustration, we flip the sign of each shock such that the median<sup>13</sup> response to the capital ratio variable is positive.

## 4. Results

We divide the discussion of results into three subsections, which loosely follows the way that we posed the identification issues in the introduction. Section 4.1 verifies that the shock processes are non-normal and subsequently disentangles the credit supply and credit demand shocks based on price and quantity impact. Section 4.2 then investigates the shocks that affect bank capital and the link between credit supply shock - identified in the previous section - and the bank capital shock. The first two sections ignore possible lending substitution effects between households and firms and between bank lending and market-based financing. Section 4.3 considers these issues.

### 4.1 Identifying credit supply and demand shocks

In order to ultimately identify bank capital shocks, we need to have the right endogenous variables, and we need to be able to disentangle credit supply and credit demand shocks. To do this, we need to be able to identify both types of shocks from the data.

Similar to Barnett and Thomas (2014), we seek to identify credit supply and credit demand shocks based on the price and quantity effect. The two core variables for our identification are the growth of bank loans and the corresponding price of credit measured by the lending spread. We also include the bank capital ratio because this is a paper primarily about bank capital shocks and we want to use the same specification in the next section. On the real side, we capture the business cycle with the industrial production (monthly data). In an extended specification, we also include two additional variables, credit quality proxied by loan losses and uncertainty proxied by the national composite index of systemic stress.

Hence, we have the following model specifications (all variables are endogenous):

1. *Capital ratio, Lending spread, Lending growth, Production growth.*
2. *Capital ratio, Lending spread, Lending growth, Production growth, SovCISS, Loan losses.*

On top of this, we consider three alternative borrower definitions: a. Firms, b. Households, c. Both; so we have altogether six alternative specifications 1a, 1b, 1c, 2a, 2b, and 2c, respectively. We estimate these S-VAR models with Monte Carlo methods assuming  $t$ -distribution for the error terms (cf. previous section). As a result, we get 15,000 draws of all the model parameters for each country including estimates for the degree

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<sup>13</sup> We calculate the median pointwise for each horizon from the set of impulse responses.

of freedom parameters  $\lambda_i$ .<sup>14</sup> Table 2 panels show the median and 10<sup>th</sup> and 90<sup>th</sup> percentile of each  $\lambda_i$  for model specifications 1a and 2a (lambdas for the four other specifications look essentially similar, so we omit them for brevity, the results are available from the authors). The degrees of freedom parameter typically ranges from around 2 to around 9 and remains mostly below 10. Recall that the required condition for identifiability is that at most one  $\lambda_i$  can be normally distributed. For example for specification 1a, Austria, Spain, Germany, Finland, Euro Area, Belgium, and France clearly satisfy this condition since their second largest median  $\lambda_i$  is well below 10. For Ireland, Portugal, Denmark, and Great Britain, the second largest  $\lambda_i$  is between 8 and 9, which are still below 10. Interestingly for specification 2a, even if there are more variables,  $\lambda_i$ s tend to be smaller and overall the non-normality properties remain similar. We conclude that the error processes display sufficiently non-normal characteristics and may proceed to analyze the identified shocks keeping in mind that there is some variation in the degree of non-normality.<sup>15</sup>

If we were to identify the model by sign-restrictions, we could specify a set of sign-restrictions {lending spread (+) and lending growth (-)} for the credit supply shock and {lending spread (+) and lending growth (+)} for the credit demand shock. Using the procedure of Arias et al. (2014) would result in a set-identified SVAR model that satisfies those restrictions. If the set of acceptable models is not too large and diverse, we can still draw impulse response bands that look somehow similar to the impulse response credible sets obtained in the Bayesian approach. However, we automatically find shocks that satisfy the sign-restrictions irrespective of whether such shocks happen to be prevalent in the data or not. This can be troublesome, for instance, if we want to investigate whether a credit supply shock has an impact on GDP or not. In contrast, with the statistical identification method, we obtain inherently unique shocks. If credit supply shocks or a credit demand shocks are relevant for the dynamics that we studying, the shocks will show up in the results given the method that we employ. Otherwise we will not find shocks that satisfy the credit demand or supply characteristics. We also underscore the fact that, as the error processes are shown to be non-normal, it is indeed appropriate to use an approach that deviates from a standard S-VAR where the errors are assumed to be normally distributed.

From the previously estimated parameters, we can calculate  $N$  draws of the impulse response function for each model specification and country. We tabulate for each shock the probability  $p$  that the shock's impact on the lending spread and lending growth is of opposite signs, the signature of a credit supply shock.<sup>16</sup> With probability  $1-p$ , the signs are the same, the signature of a credit demand shock. Table 3 shows the resulting probabilities. Higher  $p$  ( $>>0.5$ ) indicates that the shock is likely related to changes in credit supply, while lower  $p$  ( $<<0.5$ ) hints towards credit demand. In Table 3 there is evidence of both credit supply and credit

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<sup>14</sup> Recall that as the degree of freedom parameter increases, the  $t$ -distribution converges towards Normal distribution.

<sup>15</sup> To improve the robustness of the non-normality assumption for those countries that had relatively smaller deviations from normality in the error term (e.g. Great Britain and Ireland), one could consider altering the data frequency or altering the specification such that the non-normality becomes stronger. We refrain to do it here, however, to have directly comparable models for each country.

<sup>16</sup> To recapitulate, the probability  $p$  – refers to the share of drawn IRF:s with the correct sign.

demand shocks. There is somewhat stronger evidence of credit supply shocks than credit demand shocks i.e., more often  $p > 0.5$  than  $p < 0.5$ . Just by looking at the numbers the credit supply and demand shocks are also a bit more clear for the household sector than for the corporate sector. Finally, when we add the systemic stress and credit quality variables, the number of shocks and probabilities change. We get entirely new shocks and “old” shocks may change their characteristics. An example best illustrates this.

*Example: Credit Supply and Credit Demand shocks in Germany*

*Consider model 1a for Germany. The probability for each of the four shocks to be a credit supply shocks are 0.87, 0.81, 0.20, and 0.74 for shocks 1–4, respectively. Germany is a particular case in that as many as three shocks have quite high probabilities. Figure 2a shows the impulse response functions. When we add the uncertainty and credit quality, we get model 2a with the probabilities 0.78, 0.65, 0.46, 0.67, 0.28, and 0.81 for shocks 1–6, respectively. Figure 2b shows the impulse response functions. As a result of this change, shock 6, best characterized as an exogenous shock to credit quality absorbed some of the credit supply shock characteristics from shock 1, 2 and 4 of model 1a. Similarly, shock 5, best described as an exogenous shock to uncertainty, absorbed some of the credit demand shock characteristics from shock 3 of model 1a. Note that each shock number  $k$  generally has a non-zero impact at least on the  $k$ th variable, and we flipped the shocks such that the median instantaneous response of capital ratio is positive as explained at the end of Section 3.3.*

While we are interested in particular of the significance of capital shocks, we check how our model works in identifying a credit supply shock via lending standards using US data. Intuition suggests that tighter lending standards should show up in decrease in lending as is observed by Lown and Morgan (2006). The variables in our model are Lending standards, change in C&I loans, log Real GDP and Fed funds rate. Here the lending standards variable plays a role similar to our lending spread. Lown and Morgan use data for a split period 1967q1–1984q1 and 1990q2–2000q2. Here, we include four VAR lags as Lown and Morgan. We obtain the corresponding data for 1990q2–2018q1 from the Federal Reserve Bank of St. Louis. We run the Bayesian estimation, and observe again that the shocks come from non-normal distribution (see note in Figure 3). In Figure 3, shock number 2 corresponds to a lending standards shock, and can be identified as a credit supply shock. Shock number 2 satisfies the sign-relations of a credit supply shock on impact with probability 0.34, and with probability 0.99 if we allow a one year lag for the response in C&I loans. Our results are similar to the Cholesky impulse response functions found from Lown and Morgan (2006).<sup>17</sup>

To summarize Section 4.1, we can in principle disentangle credit demand and credit supply effects as long as there is evidence of both types of shocks in the data. Endogenous controls for credit quality and uncertainty

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<sup>17</sup> We also study a variation where we include Total equity to Total assets (from flow of funds). Here the bank capital shock, as in Lown and Morgan, has little or no effect on the other three variables.



appear to be relevant for characterizing credit supply and credit demand effects. With this, we are ready to proceed to the identification of bank capital shocks, the topic of the next section.

## 4.2 Identification of bank capital shocks

Throughout Section 4.2 we continue with the six specifications introduced in the previous section (1a–2c). Therefore the shocks are the same as earlier, and the previous results for the non-normality of the error process remain valid. To find out how many of the statistically identified shocks are relevant for bank capital we first run a general screen to find how many of the shocks have immediate impact on the capital ratios. Then the rest of this section investigates the properties of these shocks.

Table 4 presents two shock counts for each specification. The first count is the number of shocks for which the impact on bank capital is strictly positive with probability  $p \geq 0.99$ . The second count is similar but with a somewhat less stringent limit  $p \geq 0.95$ . The results for all the specifications (1a–2c) indicate that most of the time there is one dominant bank capital shock. Still quite frequently we identify two bank capital shocks. When we include the uncertainty and loan losses, we sometimes identify more than two shocks (cf. previous section where we found two credit supply shocks for Germany with one of them related to credit quality).

Guided by the earlier literature, we can think of two distinct shock types. A regulatory or voluntary *capital tightening* leads to higher capital ratios and potentially to reduced credit supply and reduced economic activity at least if the bank balance sheets are constrained so that credit availability is harmed. An exogenous negative *profitability shock* would have a negative effect on bank capital and could also cause a reduction in credit supply (higher margins, lower volumes) and economic activity. Note that these are both credit supply shocks (the opposite effect on price and volume). Following the earlier literature (e.g., Kanngiesser et al. (2017)), we initially assume that responses are evaluated on impact and check if all four sign-restrictions hold (towards the end of this section we relax both assumptions). To sum up, the relevant sign relations for a bank capital shock are

- *Capital tightening*: *Capital ratio* (+), *Lending spread* (+), *Lending growth* (–), *Production* (–), and
- *Profitability shock (positive)*: *Capital ratio* (+), *Lending spread* (–), *Lending growth* (+), *Production* (+).

We calculate the probability for each shock of models 1a–2c to satisfy these sign-relations. A convenient way to summarize this information, a presentation format that we will use extensively in this paper, is to calculate the number of shocks across countries that satisfy the sign-restrictions with a probability higher than some critical probability level. Table 5 shows these shocks counts when we use critical probability levels of 0.25, 0.50, 0.70, and 0.90. The top part of the table summarizes the sign relations and the counts (=number of shocks that satisfy the relations summed across all countries) for each specification follow below.

Looking first at columns 1–2 in Table 5, there is only relatively weak evidence in favor of a capital tightening or profitability shock that would have an immediate impact on all the four key variables. For example, for specification 1a column 1, in five out of the fourteen countries, there is a shock that “more likely than not” satisfies the relations ( $p \geq 0.50$ ).<sup>18</sup> However, only in a handful of cases shocks pass with a probability higher than 0.70, and in none of the cases with  $p \geq 0.90$ . The evidence is of similar quality whether we look at the firms (1a, 2a), households (1b, 2b), or at the aggregate lending (1c, 2c).

To learn more about the newly identified bank capital shocks, we now relax some of the sign-relations to investigate which sign-relations are the most relevant ones. From a practical point of view, we expect that a capital tightening shock primarily affects lending price and volumes through credit supply, which may then lead to a change in production through the availability of financing. The observed signs should then follow one of the following patterns:

- *Capital ratio (+), lending spread (+)*
- *Capital ratio (+), lending growth (–)*
- *Capital ratio (+), lending spread (+), lending growth (–)*
- *Capital ratio (+), lending spread (+), production (–)*
- *Capital ratio (+), lending growth (–), production (–)*

We expect bank profitability to work through a similar channel, so the corresponding relations are:

- *Capital ratio (+), lending spread (–)*
- *Capital ratio (+), lending growth (+)*
- *Capital ratio (+), lending spread (–), lending growth (+)*
- *Capital ratio (+), lending spread (–), production (+)*
- *Capital ratio (+), lending growth (+), production (+)*

Note that unless we specify signs for both lending spread and lending growth, we can no longer strictly distinguish between credit supply and credit demand shocks. We return to this issue in a moment.

Table 6 summarizes the probabilities to satisfy each of the above set of less restrictive sign relations. The table format is the same used previously, and the earlier results are included for comparison (columns 6 and 12 in Table 6 correspond to columns 1 and 2 in Table 5).

Table 6 shows evidence that in some countries shocks to capital ratio, whether due to capital tightening or profitability shock columns 1–2 and 7–8, respectively, have had an immediate effect on either lending spreads or volumes. In both cases, there are many shocks with  $p \geq 0.90$  for most of the specifications 1a–2c.

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<sup>18</sup> In the table we have calculated the number of shocks that satisfy the sign restrictions in each country and summed them together. Therefore the number of shocks satisfying the restrictions can sometimes be larger than the number of countries. See the last row in panel a of Table A in Appendix to see exactly where the numbers come from for model 1a.

More capital shocks have an impact on lending spread than lending volumes. Moreover, comparing specification 1a/2a and 1b/2b, the results suggest that corporate lending (either spread or volume) is more commonly (immediately) affected by these shocks than lending to households.

However, as soon as we impose more sign-restrictions, the probability to satisfy them drops sharply (see columns 3–5 or 8–10). There are still numerous shocks that satisfy three sign relations with  $p \geq 0.70$  but very few with  $p \geq 0.90$ .

Comparing the specifications 1a–c at the top of Table 6 with the specifications 2a–c at the bottom, we note that uncertainty and loan losses do not lead to different interpretation of the overall results. Only the counts change a little as a result of two opposing forces. On the one hand, the total number of shocks increases with the number of endogenous variables increasing the counts. On the other hand, some of the credit supply shocks split into generic credit supply shocks and credit supply shocks driven by exogenous shocks to credit quality. This tends to decrease the number of the high probability shocks. In fact, we checked that among the shocks that satisfy the sign-relation in Table 6 (specification 2a–2c) at  $p \geq 0.90$ , 15 % of the shocks are also related to credit quality and 10 % are related to uncertainty (overlap allowed).

Although the presentation format in Table 6 can't capture this detail, the countries with shocks most likely to satisfy some of the relaxed sign-relations are 1. Germany (most likely), 2. Belgium, 3. Spain, 4. Finland, 5. Portugal, 6. France, 7. Austria, 8. Euro Area, 9. Italy, 10. Netherlands, 11. Ireland, 12. Sweden, 13. Denmark, 14. Great-Britain (least likely).<sup>19</sup> There may not be a fundamental reason for this ordering, but some considerations include the following: Countries that suffered most in the Euro crisis are fairly evenly distributed. Germany is a large country, which typically helps in identifying shocks. None of the last three countries are members of the Euro area (possible data quality issues in the ECB data series for these countries), and Ireland has a shorter data series.

Returning to the point on credit supply and demand shocks In principle, credit demand can boost bank profits so much that the signs relations become [Capital ratio (+), lending spread (+), lending growth (–)].

Alternatively, the increased lending volumes can lead to depletion of bank capital with associated sign-relations [Capital ratio (–), lending spread (+), lending growth (+)]. We can obtain the corresponding shock counts and compare them to columns (3) and (9) of Table 6. The resulting counts are quite similar, but on average 17 percent smaller (the results are available from the authors).

As the last step, we relax the assumption that the sign relations should hold on impact. A shock to bank capital should by definition affect the bank capital on impact, but lending and production might respond with a lag. Hence, we now repeat the analysis of Tables 5–6 such that the response of lending growth, spread and production is measured one year after the shock. The results of this section culminate in Table 7, which follows the by now familiar presentation format. Interestingly, the results for capital tightening shocks

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<sup>19</sup> See Appendix A for country specific shock counts.

remain roughly similar to Table 6, but there is now clearly more evidence for profitability shocks. We propose the following interpretation. When the bank balance sheets in a country become constrained, the macro effects roll-out more or less gradually. This is observed in profitability shocks. However, banks and regulators are generally unwilling to cause negative effects on lending business so voluntary and regulatory capital increases are typically timed such that the potential negative impact on the economy is minimal. Hence, macro effects of capital tightening are less frequently observed, but when they occur, at least the effects on lending spreads and volumes may be more likely and more immediate.

To summarize Section 4.1, we find that there is varying evidence of macro effects for capital tightening and profitability shocks. The immediate effects are typically weaker and do not result in a clear change in industrial production. Quite often there are immediate effects to lending spreads or volumes while industrial production can sometimes be affected. Effects on industrial production are typically gradual. For our data period, we found that most often profitability shocks would exhibit this property with the highest levels of probability. Capital tightening shocks appear to be less relevant for the development of the real economy especially when more restrictions or variables are introduced.

#### **4.3 Reallocation of lending by bank capital shocks**

So far we considered different borrower sectors in isolation or aggregate ignoring possible substitution of lending between households and firms. Based on the literature banks are expected to shed corporate loans relative to household loans in response to tighter capital requirements, because corporate loans are on average riskier, and have higher risk weights. We also did not consider substitutes for bank lending such as security issuance. If a capital shock hampers the banking system's ability to lend to businesses, other sources of financing might proliferate to fill the gap. Next, we modify our model to investigate these issues. To catch the substitution effects between households and firms, we define relative firm lending growth and relative firm lending spread as

$$\text{Relative firm lending growth} := \text{Firm lending growth rate} - \text{Household lending growth rate, and} \quad (4.1.1)$$

$$\text{Relative firm lending spread} := \text{Firm lending spread} - \text{Household lending spread}. \quad (4.1.2)$$

To catch the substitution effects between firm's bank lending and market-based debt financing, we define lending to firms relative to bond market financing as

$$\text{Lending relative to bond markets} := \text{Firm lending growth rate} - \text{Firm bond financing growth rate}. \quad (4.1.3)$$

We do not have comparable country-specific data on corporate security interest rates, so this model is based on the capital ratio, lending volume, and production only.

The four new model specifications are

3. *Capital ratio, Relative firm lending spread, Relative firm lending growth, Production,*
4. *Capital ratio, Relative firm lending spread, Relative firm lending growth, Production, SovCISS, Corporate loan losses,*
5. *Capital ratio, Lending relative to bond markets, Production, and*
6. *Capital ratio, Lending relative to bond markets, Production, SovCISS, Corporate loan losses.*

Since we changed the specification, we need to check that the error terms fulfill the non-normality criteria. Table 8 shows the degrees of freedom parameters from the estimation results for model specifications 3–6. Overall the non-normality conditions are well satisfied. For specifications 3 and 4, at least  $n-1$  of the  $n$  error processes are clearly non-normal. Exceptions are Denmark and perhaps Portugal, which has relatively high degrees of freedom parameter estimates for the second and third highest  $\lambda_i$ . For specifications 5 and 6, the non-normality conditions are well satisfied for all countries.

For models 3–4, since we are deducting the household variables from the firm variables, the expected sign-relations are just as in the previous section. Following are the sign relations for a capital tightening shock. For a profitability shock, the signs for the other variables than the capital ratio are opposite.

- *Capital ratio (+), relative lending spread (+),*
- *Capital ratio (+), relative firm lending growth (–),*
- *Capital ratio (+), relative firm lending spread (+), relative firm lending growth (–), and*
- *Capital ratio (+), relative firm lending spread (+), production (–).*
- *Capital ratio (+), relative firm lending growth (–), production (–)*
- *Capital ratio (+), relative firm lending spread (+), relative firm lending growth (–), production (–)*

For models 5–6, there is no spread so there are only two sign-relations to be checked

- *Capital ratio (+), lending relative to bond markets (–), and*
- *Capital ratio (+), lending relative to bond markets (–), production (–).*

Table 9 panels a) and b) present the shock counts for models 3–4 and 5–6, respectively, following the familiar format (cf. previous section). In panel a), we find evidence of bank capital shocks that lead to a substitution of lending between sectors (counts that are  $\gg 1$  for  $p \geq 0.90$ ). The relative lending spread or the relative lending growth is quite often affected by the bank capital shock with high probability even if these numbers tend to be slightly smaller than in the previous section. As the number of sign relations grows, the probability of satisfying those decays fast (see rows  $p \geq 0.70$  or  $0.90$  and columns other than 1–2 and 7–8). Interestingly, at least in the sample capital tightening shocks have more often a substitution effect on lending volumes than on lending spreads (compare columns 1 and 2). The effects of tightening tend to be immediate since the counts remain the same whether we look at the immediate or lagged responses. In contrast,

profitability shocks tend to have more often immediate impact on the spread and only later some impact on the volume (compare columns 7 and 8). Like observed in Section 3.2 the impact on production is limited.

During the data period, the countries with capital shocks most likely to induce firm–household substitution were 1. France, 2. Spain, 3. Belgium, 4. Germany, 5. Ireland, 6. Austria, 7. Euro area, 8. Sweden, 9. Finland, 10. Portugal, 11. Netherlands, 12. Great Britain, 13. Denmark, 14. Italy. Figure 4 illustrates model 4 for the French case. For example, shock 1 satisfies the sign relations (Capital ratio +, Relative lending growth –) with probability 0.98, and shock 2 satisfied the sign relations (Capital ratio +, Relative spread +) with probability 0.94.

As we turn to Table 9 panel b), note that models 5–6 are ran only for ten countries due to data availability issues. Taking into account the smaller number of countries, the evidence for substitution between bank lending and corporate bond issuance is at least similar as or slightly stronger than for substitution between household and firm borrowers (see in particular the rows with  $p \geq 0.70$  or 0.90). For both capital tightening and profitability shocks, there is evidence of both immediate and lagged impact on lending relative to bond markets. In both cases the lagged impact is more frequently observed than immediate impact.<sup>20</sup>

During the data period, the countries with capital shocks most likely to induce this type of substitution were 1. France, 2. Germany, 3. Netherlands, 4. Portugal, 5. Italy, 6. Belgium, 7. Austria, 8. Finland, 9. Euro area, 10. Spain. Figure 5 illustrates model 5 for the French case. In this case shock 1 satisfies the sign relations (Capital ratio +, Lending relative to bond markets –) with probability 0.99 and the sign relations (Capital ratio +, Lending relative to bond markets –, Production –) with probability 0.98.

To sum up Section 4.3, we find evidence for both firm–household and bank–market-finance substitution effects as a consequence of bank capital shocks. Still, it is rare to satisfy more than two sign-relations simultaneously with high probability. Even if the transmission channel is essentially the same, the dynamic tends to evolve differently depending on whether the initial shock is a profitability shock or capital tightening shock. Capital tightening has more immediate effects on relative lending volumes while profitability shocks have a more immediate effect on spreads. Capital and profitability shocks also can have an impact on the substitution of lending between banks and other financial intermediaries.

#### **4.4 Robustness checks – inflation and monetary policy**

Many earlier papers included short-term interest rate (a proxy for monetary policy) and inflation in the VAR model. As a robustness check, we expand models 1a–2c and 4–6 to incorporate these variables such that the short-term interest rate enters exogenously except for the Euro Area aggregate.

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<sup>20</sup> Note that here lagged impact and immediate impact are not mutually exclusive, since we only look at the impulse response at either  $t=0$  or  $t=12$ .

The posterior distribution of degrees of freedom parameters for models 1a and 2a are shown in Table 10 (for brevity we again omit the  $\lambda_i$ 's for the other four specifications 1b–2c). They remain similar to what was found before with typical values ranging from 2 to 9. Observing that the second highest  $\lambda_i$ 's are again typically well below 10, we conclude that the shocks seem to satisfy the non-normality criteria.

Table 11 presents the counts of shocks satisfying each combination of sign-relations related to bank capital shocks (cf. Table 6). The counts with lower probability thresholds are now markedly higher due to the increased number of variables. However, the number of shocks that satisfy the relations with a high probability remain in the same range as earlier, so our earlier conclusions remain valid.

Tables 12 and 13 repeat similar robustness checks for the substitution effect analysis. Again there is a small change in the counts, but overall our results still hold.

## 5. Discussion

We have identified bank capital shocks based on the non-normal distributional properties of the error terms using the novel method by Lanne et al. We disentangle the credit supply and credit demand shocks, and use proxies for credit quality and uncertainty to control for endogenous supply and demand effects beyond the aggregate production. We find shocks that in terms of real effects, most of the time, are not as effective as bank capital shocks postulated in the sign-restricted VAR papers (e.g., Kanngiesser et al. 2017). Only in rare cases, all the sign-relations are satisfied with high probability. Often there is a definite impact on one banking variable only, the spread or volume, while other times the only variable affected by the bank capital shock is the bank capital itself. In this sense, the results fall between the sign-restricted VAR literature and the earlier literature that used Cholesky decomposition (e.g., Berrospide and Edge 2010, Lown and Morgan 2006) and found that bank capital shocks have a modest impact on real economy.

The paper has decidedly European focus as we run the analysis separately for fourteen European economies (including the Euro Area). Macroprudential policies may be more useful in the monetary union where individual countries have partly given up their powers to influence financing conditions through monetary policy. Europe has also been at the forefront of implementing Basel III including various new capital buffers, some of them with the aim to directly impact the credit supply through bank capital increases in order to tame costly credit booms. The fact that results are country-dependent is not surprising given that there are many banks in Europe that operate first and foremost domestically. Our results suggest that forecasting the impact of capital buffer adjustments is not very straightforward. There can be a significant impact to lending spreads and volumes as well as substitution between different types of borrowers and lenders or different sources of credit intermediation. Judging the likely impact will require details of the supply and demand factors in the national financing market. Factors such as banking sector capitalization, business model, earnings, and competition for borrowers may affect how capital increases channel into lending and real economy.

Moreover, the fact that in the real world occurrence of credit demand shocks and credit supply shocks may be highly correlated further hampers empirical identification. It is worth investigating whether bank lending surveys can improve the identification further. However, given Lucas critique and regulators tendency to avoid real economic costs, a more structured approach that can take into account the many details of the corresponding banking sector should be useful for practitioners.

Our analysis on bank capital shocks should be useful for theory builders and regulators alike who wish to understand the interaction between bank capital and macroeconomy. Differences across countries may mandate the use of country-specific variables. This is beyond the scope of our paper, but authorities who wish to use this method to study bank capital shocks in their country may benefit from alternative country-specific series for lending standards, risk-weighted capital ratios, credit quality, and lending margins. For example, we recently used the supervisors' proprietary data for risk-weighted capital ratios, the Bank of Finland data of loan-by-loan lending margins, lending volumes, and real GDP to run a quarterly model (identified as here) for Finland. The results confirmed the predominant view that the recent hefty increases in Finnish bank capital ratios have not had significant adverse effects on credit supply.

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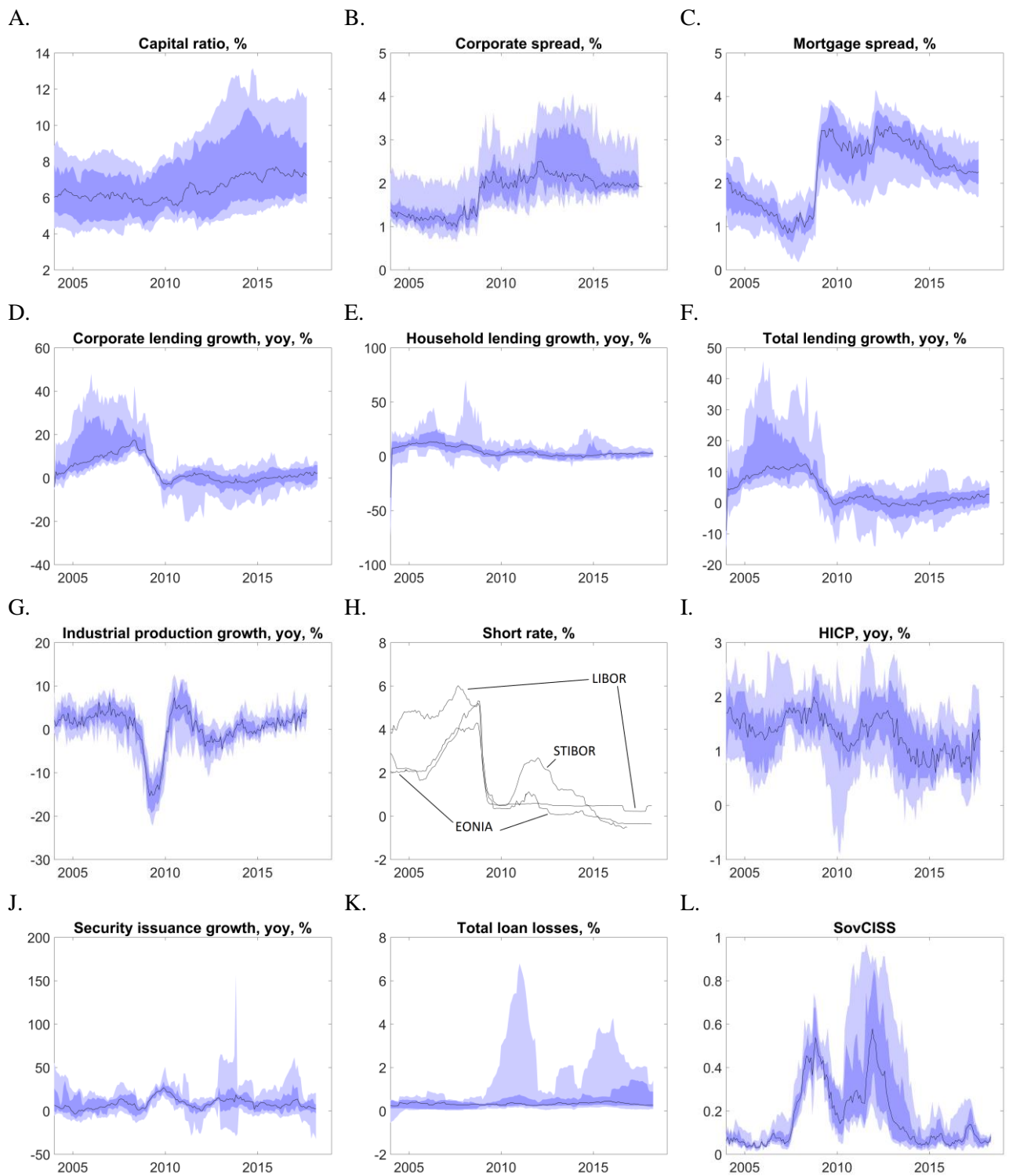
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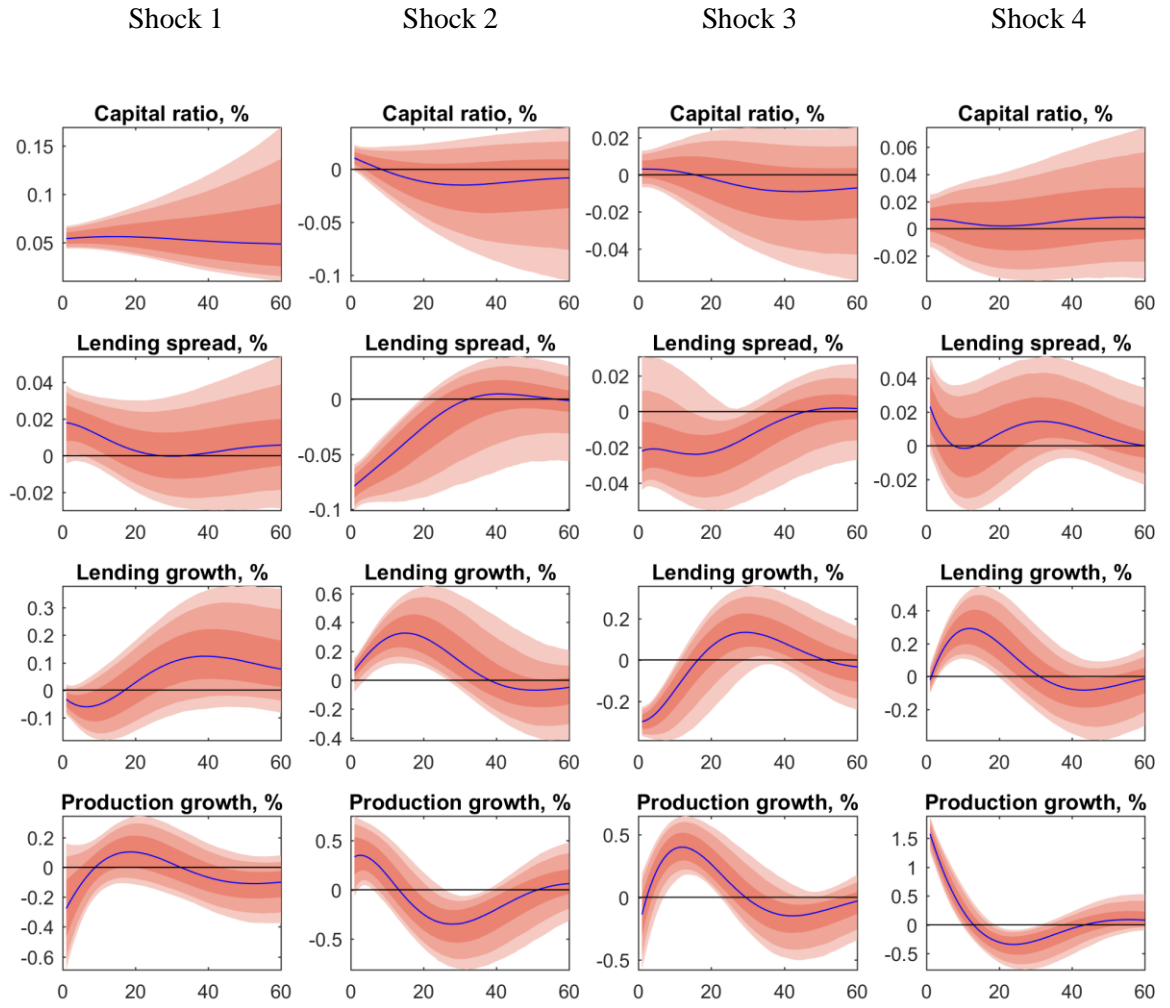




**Figure 1. Descriptive graphics.** Medians and percentile bands for variables. The line shows the median and light and dark areas show the 25–75 percentile range and the 10–90 percentile range, respectively. 1H directly shows the EONIA, O/N Stibor, and O/N Libor.

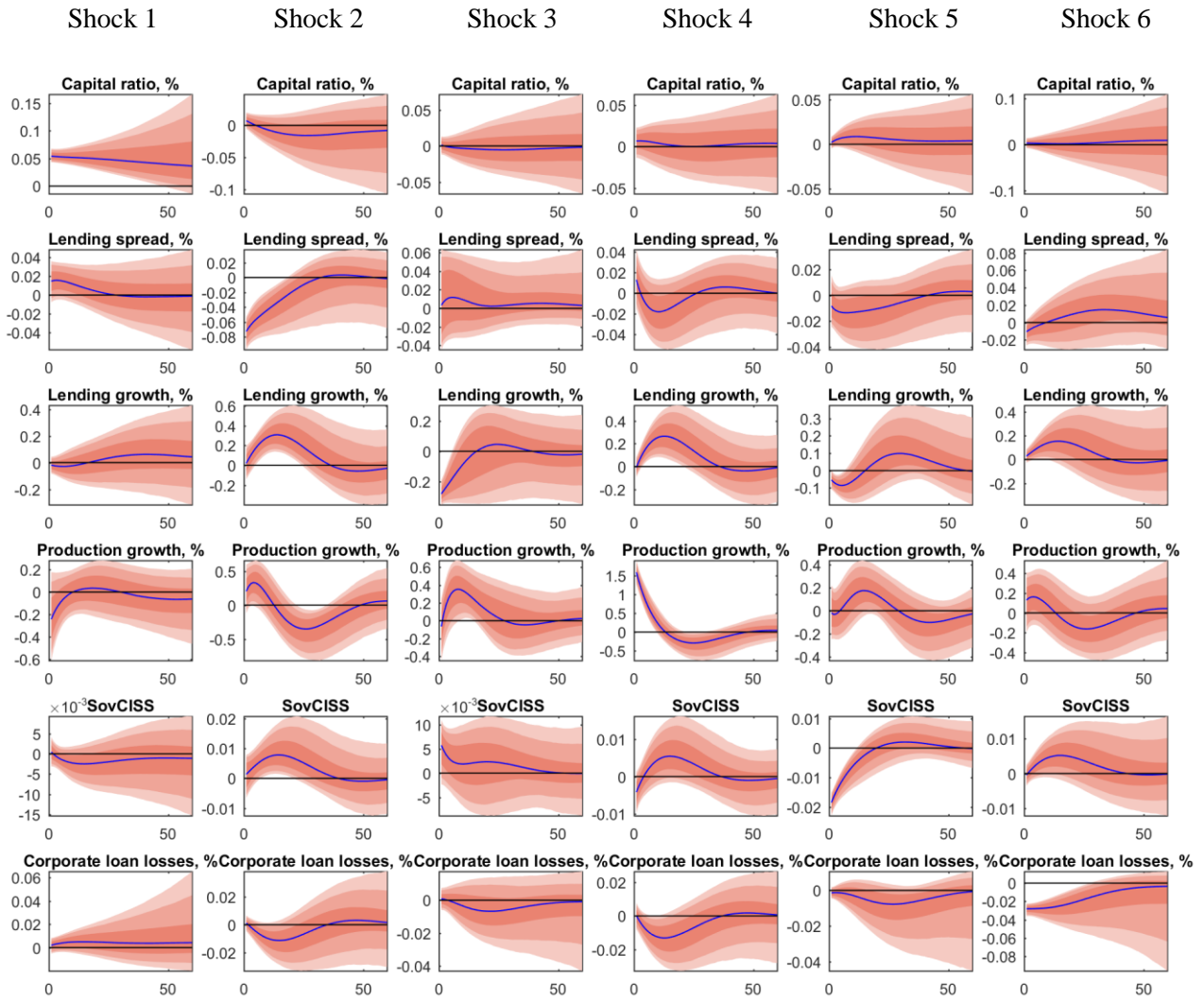
**Figure 2. Example shocks – Germany.** The fan charts show the posterior median<sup>21</sup> (blue line) and 68 %, 90 %, and 95 % credible sets (different shadings of red).

**a) Model 1a**

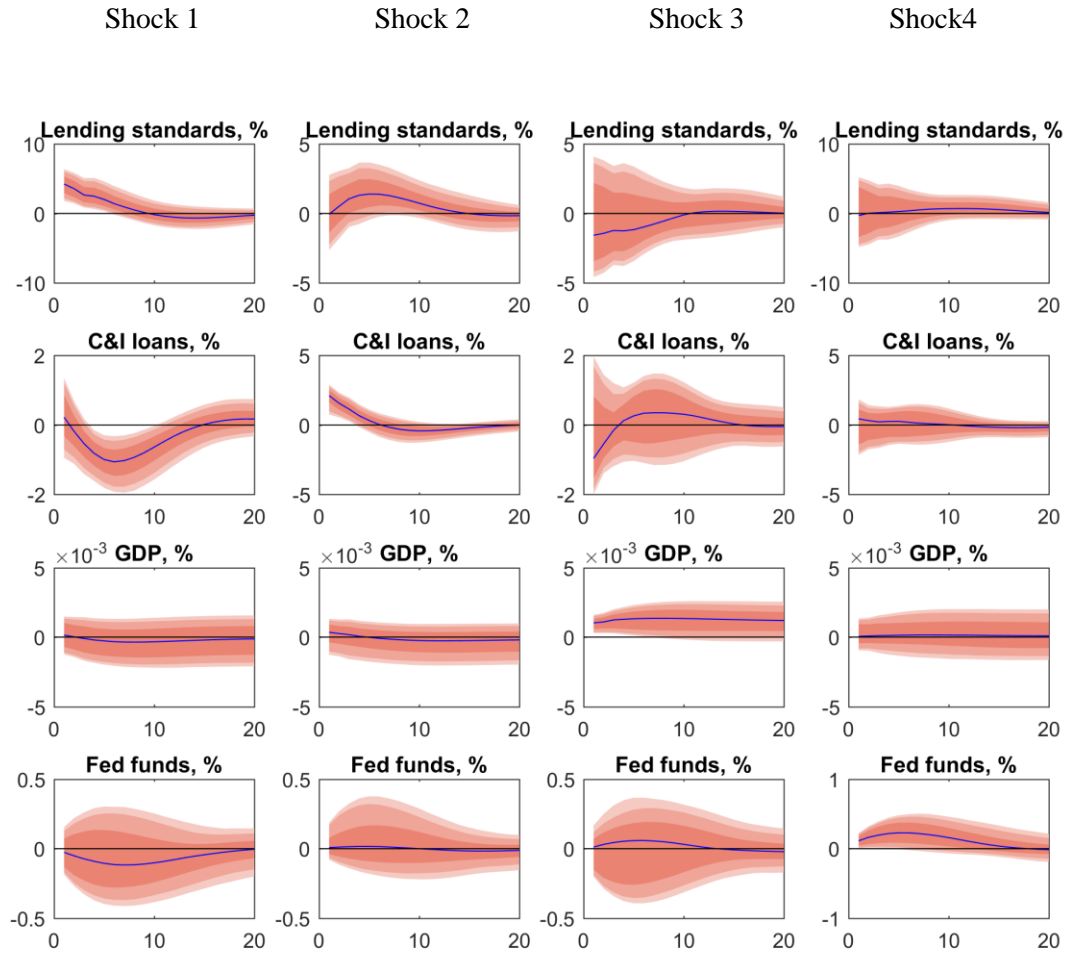


<sup>21</sup> The median and the credible sets displayed are calculated pointwise for each horizon from the set of impulse responses. We employ the same calculation in all the figures that display medians or credible sets.

## b) Model 2a



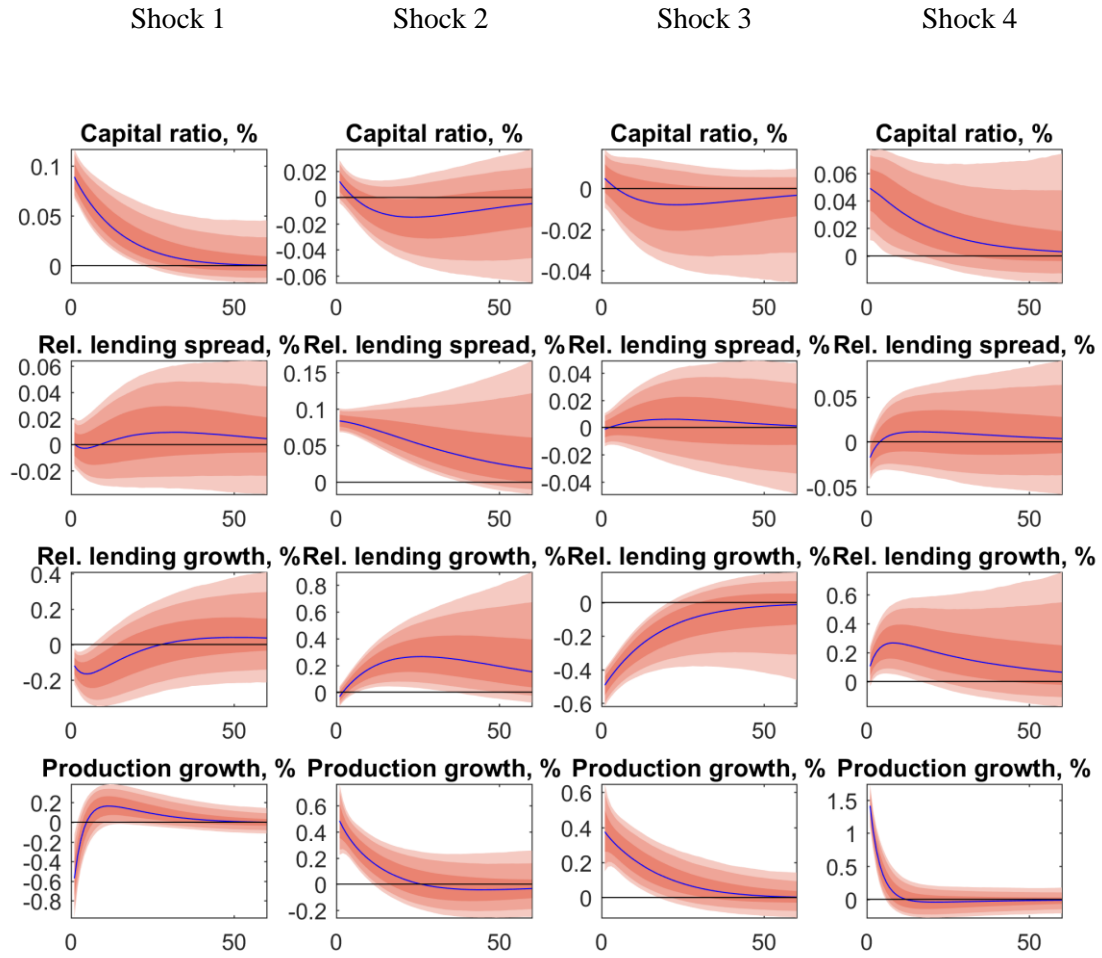
**Figure 3. Comparison to Lown and Morgan (2006).** The fan charts show the posterior median (blue line) and 68 %, 90 %, and 95 % credible sets (different shadings of red).



Posterior estimates for degrees of freedom parameters of the t-distributed error terms for the Lown and Morgan model.

$\lambda_{1,p50}$	$\lambda_{1,p10}$	$\lambda_{1,p90}$	$\lambda_{2,p50}$	$\lambda_{2,p10}$	$\lambda_{2,p90}$	$\lambda_{3,p50}$	$\lambda_{3,p10}$	$\lambda_{3,p90}$	$\lambda_{4,p50}$	$\lambda_{4,p10}$	$\lambda_{4,p90}$
<b>4.2</b>	2.3	10.9	<b>4.8</b>	2.7	9.6	<b>4.1</b>	2.5	8.2	<b>4.4</b>	2.4	11.1

**Figure 4. Example shocks – France, model 3.** The fan charts show the posterior median (blue line) and 68 %, 90 %, and 95 % credible sets (different shadings of red).

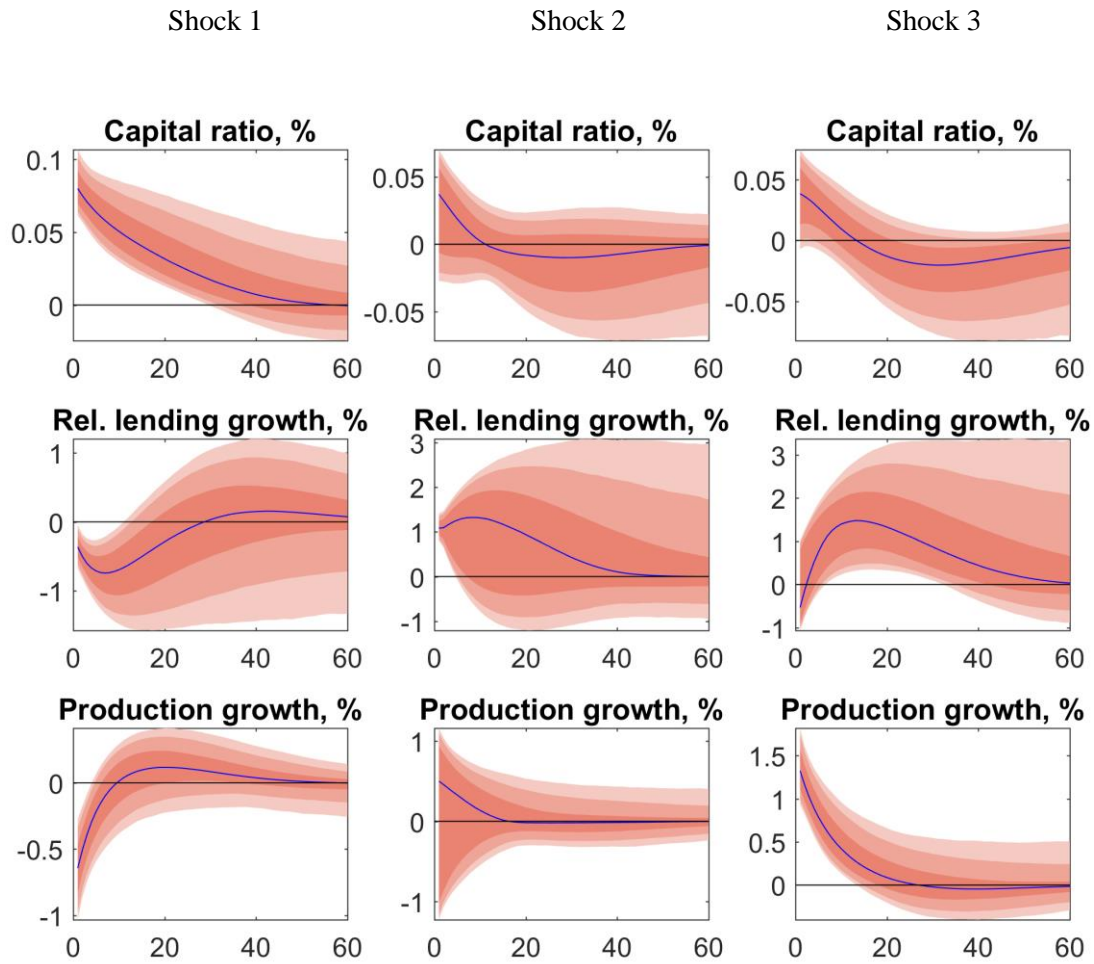


Probabilities for the above impulse response functions to satisfy specific sign-relations at  $t=0$ .

	Capital tightening (1–6)						Profitability shock (7–12)					
Sign relations:												
<i>Capital ratio</i>	+	+	+	+	+	+	+	+	+	+	+	+
<i>Relative firm lending spread</i>	+		+	+		+	–		–	–		–
<i>Relative firm lending growth</i>		–	–		–	–		+	+		+	+
<i>Production</i>				–	–	–				+	+	+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
3. <i>Capital ratio, Relative firm lending spread, Relative firm lending growth, Production</i>												
Shock 1	0.53	0.98	0.53	0.53	0.97	0.53	0.47	0.02	0.02	0.02	0.01	0.01
Shock 2	0.94	0.80	0.79	0.00	0.00	0.00	0.06	0.20	0.05	0.00	0.15	0.00
Shock 3	0.45	0.77	0.00	0.45	0.77	0.00	0.55	0.23	0.09	0.46	0.00	0.00
Shock 4	0.09	0.08	0.01	0.00	0.00	0.02	0.91	0.92	0.86	0.90	0.92	0.86

**Figure 5. Example shocks – France, model 5**

. The fan charts show the posterior median (blue line) and 68 %, 90 %, and 95 % credible sets (different shadings of red).



Probabilities for the above impulse response functions to satisfy specific sign-relations at  $t=0$ .

	Capital tightening (1–2)		Profitability shock (3–4)	
Sign relations:				
<i>Capital ratio</i>	+	+	+	+
<i>Lending relative to bond markets</i>	–	–	+	+
<i>Production</i>		–		+
	(1)	(2)	(3)	(4)
5. <i>Capital ratio, Lending relative to bond markets, Production</i>				
Shock 1	0.99	0.98	0.01	0.00
Shock 2	0.17	0.17	0.83	0.70
Shock 3	0.64	0.00	0.36	0.30



**Table 1. Variables definitions and sources.**

Variable	Definition	Detailed definition	SDW series code
Industrial production growth, %	Industrial production; total including construction	Industrial Production Index, Total Industry - NACE Rev2; Eurostat; Working day and seasonally adjusted; Annual growth rate	STS.M.*.Y.PROD.NS0010.4.000
Core inflation, %	HICP - All-items excluding energy and food	HICP - All-items excluding energy and food, Annual rate of change, Eurostat, Neither seasonally nor working day adjusted	ICP.M.*.N.XEF000.4.ANR
Short rate, %	Short money market rate	The average overnight interest rate during one month period. Euro Overnight Index Area for euro zone countries; O/N libor for GB; O/N Stibor for SE.	
Corporate loan growth, %	Loans vis-a-vis domestic NFC reported by MFI excluding ESCB	Annual growth rate calculated from Index of Notional Stocks, MFIs excluding ESCB reporting sector - loans to Euro Area non-financial corporations, Annual growth rate, Neither seasonally nor working day adjusted	BSI.M.*.N.A.A20.A.I.U2.2240.Z01.E
Consumer loan growth, %	Loans vis-a-vis domestic HH reported by MFI excluding ESCB	Annual growth rate calculated from Index of Notional Stocks, MFIs excluding ESCB reporting sector - loans to Euro Area Households and non-profit institutions serving households, Annual growth rate, Neither seasonally nor working day adjusted	BSI.M.*.N.A.A20.A.I.U2.2250.Z01.E
Corporate spread, bps	Bank interest rates - loans to corporations (new business) LESS Short money market rate	Annualised agreed rate (AAR) / Narrowly defined effective rate (NDER), Credit and other institutions (MFI except MMFs and central banks) reporting sector - Loans other than revolving loans and overdrafts, convenience and extended credit card debt, Total initial rate fixation, Total amount, New business coverage, Non-Financial corporations (S.11) sector, denominated in Euro	MIR.M.*.B.A2A.A.R.A.2240.EUR.N
Mortgage spread, bps	Bank interest rates - loans to households for house purchase (new business) LESS Short money market rate	Annualised agreed rate (AAR) / Narrowly defined effective rate (NDER), Credit and other institutions (MFI except MMFs and central banks) reporting sector - Lending for house purchase excluding revolving loans and overdrafts, convenience and extended credit card debt, Total initial rate fixation, New business coverage, Households and non-profit institutions serving households, denominated in Euro	MIR.M.*.B.A2C.A.R.A.2250.EUR.N, MIR.M.SE.B.A22.A.R.A.2250.SEK.O
Capital ratio, %	Capital and reserves reported by MFI excluding ESCB (stock) DIVIDED BY Total Assets (or Liabilities) reported by MFI excluding ESCB (stock)	Outstanding amounts at the end of the period (stocks), MFIs excluding ESCB reporting sector - Capital and reserves, Total Assets/Liabilities, Neither seasonally nor working day adjusted	BSI.M.*.N.A.L60.X.1.Z5.0000.Z01.E, BSI.M.*.N.A.T00.A.1.Z5.0000.Z01.E
Corporate loan losses, %	Cumulative 12 month corporate loan losses DIVIDED BY the corporate loan stock	Cumulative 12 month other adjustments, MFIs excluding ESCB reporting sector - Loans to Euro area (changing composition) non-financial corporations, denominated in Euro, data Neither seasonally nor working day adjusted DIVIDED BY Outstanding amounts at the end of the period (stocks), MFIs excluding ESCB reporting sector - Euro area (changing composition) counterpart, Households and non-profit institutions serving households, denominated in Euro, data Neither seasonally nor working day adjusted	BSI.M.*.N.A.A20.A.7.U2.2240.Z01.E, BSI.M.*.N.A.A20.A.1.U2.2250.Z01.E
Household loan losses, %	Cumulative 12 month household loan losses DIVIDED BY the household loan stock	Cumulative 12 month other adjustments, MFIs excluding ESCB reporting sector - Loans to Euro area (changing composition) households and non-profit institutions serving households, denominated in Euro, data Neither seasonally nor working day adjusted DIVIDED BY Outstanding amounts at the end of the period (stocks), MFIs excluding ESCB reporting sector - Euro area (changing composition) counterpart, Non-Financial corporations, denominated in Euro, data Neither seasonally nor working day adjusted	BSI.M.*.N.A.A20.A.7.U2.2250.Z01.E, BSI.M.*.N.A.A20.A.1.U2.2250.Z01.E
SovCISS, Index	Composite Indicator of Sovereign Stress	Country specific composite stress indicator, Index	CISS.M.*.Z0Z.4F.EC.SOV_CI.IDX

**Table 2. Posterior estimates for degrees of freedom parameter (capital shock models).** The error process is assumed to follow t-distribution. Table shows the posterior estimates of the degree of freedom parameter  $\lambda_k$  of each error component for specifications 1a and 2a.

Country	EA	DE	FR	GB	IT	ES	FI	SE	DK	AT	BE	NL	PT	IE
<i>T</i>	162	161	161	161	161	161	161	135	161	161	161	161	161	93
<i>1a. Capital ratio, Corporate spread, Corporate lending, Production</i>														
$\lambda_{1,p50}$	<b>4.4</b>	<b>3.3</b>	<b>4.3</b>	<b>10.3</b>	<b>2.3</b>	<b>2.8</b>	<b>3.3</b>	<b>3.9</b>	<b>8.2</b>	<b>2.4</b>	<b>2.3</b>	<b>2.5</b>	<b>2.5</b>	<b>2.4</b>
$\lambda_{1,p10}$	2.8	2.4	2.7	5.4	2.0	2.2	2.4	2.6	4.7	2.1	2.1	2.1	2.1	2.1
$\lambda_{1,p90}$	8.7	5.0	8.0	19.8	2.8	3.8	5.0	7.6	15.1	3.1	3.0	3.3	3.2	3.1
$\lambda_{2,p50}$	<b>3.2</b>	<b>3.2</b>	<b>4.2</b>	<b>6.6</b>	<b>7.0</b>	<b>4.0</b>	<b>7.5</b>	<b>6.6</b>	<b>8.6</b>	<b>3.1</b>	<b>5.4</b>	<b>6.8</b>	<b>9.2</b>	<b>5.8</b>
$\lambda_{2,p10}$	2.3	2.3	2.6	3.9	3.9	2.7	4.5	3.8	4.7	2.3	3.3	3.6	4.9	3.1
$\lambda_{2,p90}$	4.9	5.5	8.2	12.6	13.9	6.4	15.1	13.1	16.7	4.8	9.9	13.8	18.3	13.1
$\lambda_{3,p50}$	<b>5.3</b>	<b>4.1</b>	<b>6.1</b>	<b>8.9</b>	<b>7.6</b>	<b>5.5</b>	<b>3.1</b>	<b>2.4</b>	<b>2.5</b>	<b>3.6</b>	<b>2.9</b>	<b>6.5</b>	<b>6.6</b>	<b>8.2</b>
$\lambda_{3,p10}$	3.2	2.8	3.3	4.5	4.3	3.4	2.3	2.1	2.1	2.6	2.2	3.7	3.7	4.0
$\lambda_{3,p90}$	10.2	6.6	12.1	17.2	15.1	10.1	4.9	3.2	3.4	5.4	4.4	12.8	13.0	16.4
$\lambda_{4,p50}$	<b>9.8</b>	<b>8.5</b>	<b>9.8</b>	<b>5.8</b>	<b>6.8</b>	<b>2.6</b>	<b>4.8</b>	<b>11.5</b>	<b>8.5</b>	<b>10.5</b>	<b>6.1</b>	<b>9.2</b>	<b>8.4</b>	<b>8.4</b>
$\lambda_{4,p10}$	5.3	4.7	5.5	3.3	4.1	2.1	3.0	6.1	4.7	5.7	3.7	5.0	4.6	4.3
$\lambda_{4,p90}$	19.1	15.8	18.3	12.2	13.1	3.5	9.0	21.4	15.5	20.3	11.1	18.6	17.2	16.8
<i>2a. Capital ratio, Corporate spread, Corporate lending, Production, SovCISS, Corporate loan losses</i>														
$\lambda_{1,p50}$	<b>4.2</b>	<b>3.3</b>	<b>4.3</b>	<b>9.1</b>	<b>2.3</b>	<b>2.7</b>	<b>3.1</b>	<b>4.1</b>	<b>9.1</b>	<b>2.4</b>	<b>2.2</b>	<b>2.4</b>	<b>2.3</b>	<b>2.3</b>
$\lambda_{1,p10}$	2.6	2.4	2.8	4.8	2.0	2.2	2.3	2.5	5.2	2.1	2.0	2.1	2.0	2.0
$\lambda_{1,p90}$	8.2	5.3	7.6	18.3	2.8	3.6	4.4	8.1	17.2	3.0	2.8	3.1	2.8	2.9
$\lambda_{2,p50}$	<b>2.5</b>	<b>2.9</b>	<b>3.9</b>	<b>6.6</b>	<b>7.0</b>	<b>3.9</b>	<b>7.7</b>	<b>6.8</b>	<b>9.9</b>	<b>2.8</b>	<b>6.4</b>	<b>3.4</b>	<b>5.4</b>	<b>3.0</b>
$\lambda_{2,p10}$	2.1	2.2	2.6	3.9	3.9	2.6	4.4	3.6	5.3	2.2	3.5	2.2	3.2	2.1
$\lambda_{2,p90}$	3.4	5.1	7.1	13.0	15.2	6.9	14.8	15.7	19.3	4.2	14.1	10.0	10.8	9.7
$\lambda_{3,p50}$	<b>5.3</b>	<b>4.2</b>	<b>5.3</b>	<b>5.9</b>	<b>6.4</b>	<b>7.2</b>	<b>3.3</b>	<b>2.4</b>	<b>2.5</b>	<b>3.5</b>	<b>2.9</b>	<b>5.1</b>	<b>4.7</b>	<b>8.2</b>
$\lambda_{3,p10}$	3.2	2.7	3.1	3.3	3.7	4.0	2.3	2.1	2.1	2.5	2.2	2.5	2.9	3.8
$\lambda_{3,p90}$	9.9	7.2	10.5	13.5	12.3	13.7	5.7	3.3	3.3	5.2	4.3	10.7	9.0	17.5
$\lambda_{4,p50}$	<b>5.3</b>	<b>7.4</b>	<b>9.7</b>	<b>7.1</b>	<b>5.9</b>	<b>2.6</b>	<b>6.4</b>	<b>11.3</b>	<b>7.7</b>	<b>10.4</b>	<b>5.6</b>	<b>9.2</b>	<b>7.8</b>	<b>8.1</b>
$\lambda_{4,p10}$	2.8	4.3	5.3	4.0	3.6	2.1	3.7	5.7	4.2	5.7	3.4	4.8	4.4	3.8
$\lambda_{4,p90}$	12.8	13.8	18.6	15.5	10.4	3.4	12.7	21.4	15.7	19.1	9.7	17.8	15.1	17.1
$\lambda_{5,p50}$	<b>4.3</b>	<b>2.2</b>	<b>2.3</b>	<b>2.4</b>	<b>2.4</b>	<b>2.4</b>	<b>2.3</b>	<b>2.3</b>	<b>2.5</b>	<b>2.2</b>	<b>2.1</b>	<b>5.2</b>	<b>5.9</b>	<b>3.3</b>
$\lambda_{5,p10}$	2.5	2.0	2.0	2.1	2.1	2.1	2.1	2.1	2.1	2.0	2.0	2.4	3.3	2.1
$\lambda_{5,p90}$	10.4	2.8	2.8	3.3	3.0	3.2	2.9	2.9	3.2	2.5	2.4	12.3	12.1	11.7
$\lambda_{6,p50}$	<b>2.1</b>	<b>2.7</b>	<b>2.3</b>	-	<b>2.1</b>	<b>2.0</b>	<b>2.1</b>	-	-	<b>2.3</b>	<b>2.2</b>	<b>2.2</b>	<b>2.1</b>	<b>2.0</b>
$\lambda_{6,p10}$	2.0	2.1	2.1	-	2.0	2.0	2.0	-	-	2.0	2.0	2.0	2.0	2.0
$\lambda_{6,p90}$	2.4	4.2	3.0	-	2.2	2.1	2.4	-	-	2.8	2.7	2.5	2.3	2.1

*T* is the number of monthly observations.

Loan loss data is available only for Euro Area countries.

**Table 3. Credit supply and credit demand shocks.** Based on posterior estimates for models 1a–2c, table shows probability  $p$  for each shock to satisfy (on impact) the sign relations of a credit supply shock, i.e. opposite sign response for price and quantity of credit, is presented. The complement  $1-p$  is the probability to satisfy the sign relations of credit demand shock.

Country	EA	DE	FR	GB	IT	ES	FI	SE	DK	AT	BE	NL	PT	IE
<i>1a. Capital ratio, Corporate spread, Corporate lending, Production</i>														
Shock 1	0.54	0.87	0.36	0.36	0.61	0.95	0.25	0.50	0.59	0.20	0.30	0.90	0.63	0.55
Shock 2	0.59	0.81	0.17	0.86	0.65	0.64	0.93	0.32	0.33	0.63	0.91	0.41	0.79	0.64
Shock 3	0.64	0.20	0.83	0.35	0.40	0.89	0.26	0.88	0.72	0.71	0.05	0.51	0.37	0.76
Shock 4	0.78	0.74	0.40	0.46	0.78	0.15	0.34	0.71	0.38	0.58	0.71	0.34	0.41	0.60
<i>1b. Capital ratio, Household spread, Household lending, Production</i>														
Shock 1	0.41	0.67	0.71	0.61	0.49	0.69	0.59	0.48	0.50	0.58	0.62	0.92	0.48	0.80
Shock 2	1.00	0.51	1.00	0.29	1.00	0.36	1.00	0.46	0.84	0.57	0.34	0.35	1.00	0.56
Shock 3	0.04	0.18	0.36	0.85	0.04	0.91	0.02	0.37	0.59	0.12	1.00	0.32	0.62	0.66
Shock 4	0.20	0.36	0.03	0.69	0.11	0.90	0.01	0.37	0.52	0.86	0.52	0.79	0.36	0.58
<i>1c. Capital ratio, Aggregate spread, Aggregate lending, Production</i>														
Shock 1	0.49	0.83	0.18	0.64	0.66	0.92	0.48	0.49	0.43	0.05	0.63	0.28	0.76	0.63
Shock 2	0.99	0.19	0.91	0.26	0.86	0.90	0.98	0.35	0.65	0.95	0.59	0.16	0.96	0.37
Shock 3	0.32	0.81	0.57	0.88	0.35	0.66	0.10	0.87	0.57	0.14	0.93	0.85	0.23	0.66
Shock 4	0.82	0.90	0.37	0.61	0.61	0.31	0.40	0.73	0.46	0.72	0.37	0.50	0.23	0.71
<i>2a. Capital ratio, Corporate spread, Corporate lending, Production, SovCISS, Corporate loan losses</i>														
Shock 1	0.45	0.78	0.15	0.37	0.57	0.92	0.58	0.31	0.62	0.14	0.22	0.86	0.33	0.51
Shock 2	0.46	0.65	0.30	0.88	0.75	0.30	0.37	0.93	0.47	0.75	0.92	0.44	0.84	0.39
Shock 3	0.43	0.46	0.77	0.26	0.35	0.96	0.84	0.25	0.70	0.67	0.02	0.44	0.34	0.85
Shock 4	0.72	0.67	0.46	0.62	0.65	0.17	0.71	0.39	0.46	0.54	0.63	0.42	0.50	0.55
Shock 5	0.82	0.28	0.15	0.57	0.39	0.53	0.56	0.10	0.13	0.43	0.37	0.58	0.59	0.77
Shock 6	0.58	0.81	0.31	-	0.33	0.81	-	0.54	-	0.68	0.83	0.79	0.84	0.78
<i>2b. Capital ratio, Household spread, Household lending, Production, SovCISS, Household loan losses</i>														
Shock 1	0.21	0.73	0.67	0.55	0.50	0.69	0.48	0.58	0.53	0.57	0.67	0.90	0.39	0.79
Shock 2	1.00	0.62	1.00	0.21	0.94	0.37	0.43	0.94	0.81	0.64	0.41	0.32	0.99	0.50
Shock 3	0.00	0.21	0.31	0.81	0.09	0.96	0.28	0.13	0.54	0.12	0.98	0.20	0.48	0.81
Shock 4	0.25	0.40	0.53	0.75	0.28	0.57	0.39	0.10	0.58	0.70	0.56	0.57	0.35	0.64
Shock 5	0.80	0.20	0.36	0.75	0.43	0.45	0.52	0.67	0.54	0.65	0.61	0.64	0.54	0.58
Shock 6	0.11	0.35	0.06	-	0.47	0.58	-	0.69	-	0.45	0.40	0.82	0.56	0.57
<i>2c. Capital ratio, Aggregate spread, Aggregate lending, Production, SovCISS, Aggregate loan losses</i>														
Shock 1	0.51	0.82	0.40	0.54	0.61	0.92	0.57	0.49	0.56	0.04	0.65	0.24	0.41	0.63
Shock 2	0.98	0.81	0.82	0.38	0.82	0.59	0.41	0.92	0.68	0.91	0.70	0.67	0.54	0.18
Shock 3	0.14	0.11	0.54	0.69	0.38	0.94	0.84	0.14	0.54	0.15	0.54	0.28	0.20	0.89
Shock 4	0.25	0.69	0.37	0.80	0.51	0.25	0.71	0.45	0.53	0.69	0.47	0.54	0.36	0.80
Shock 5	0.64	0.80	0.13	0.74	0.58	0.26	0.54	0.32	0.15	0.54	0.31	0.85	0.96	0.66
Shock 6	0.58	0.76	0.31	-	0.43	0.66	-	0.70	-	0.62	0.64	0.87	0.70	0.84

Loan loss data is available only for Euro Area countries.

The data is based on 15,000 Monte Carlo draws of the hierarchical Bayesian SVAR model with t-distributed error terms. The estimation is performed independently for each country. The numbering of shocks is such that the  $i$ th shock typically has highest impact on the  $i$ th variable (cf. bla-bla-bla).

**Table 4. Number of bank capital shocks.** Based on posterior estimates of the impulse response function, Table shows the number of shocks that have strictly positive (instantaneous) impact on capital ratio is positive with probability  $p$  higher than 0.95 or 0.99.

Country	EA	DE	FR	GB	IT	ES	FI	SE	DK	AT	BE	NL	PT	IE
<i>1a. Capital ratio, Corporate spread, Corporate lending, Production</i>														
$p \geq 0.99$	1	1	1	1	1	1	1	1	1	2	2	1	1	1
$p \geq 0.95$	1	2	1	1	1	1	1	1	1	2	2	2	2	1
<i>1b. Capital ratio, Household spread, Household lending, Production</i>														
$p \geq 0.99$	1	1	1	1	1	2	1	1	1	1	2	1	1	1
$p \geq 0.95$	1	2	1	1	1	2	1	2	1	1	2	1	1	1
<i>1c. Capital ratio, Aggregate spread, Aggregate lending, Production</i>														
$p \geq 0.99$	1	1	1	1	1	1	1	1	1	2	2	2	1	1
$p \geq 0.95$	1	1	2	1	1	1	1	1	1	2	2	2	2	1
<i>2a. Capital ratio, Corporate spread, Corporate lending, Production, SovCISS, Corporate loan losses</i>														
$p \geq 0.99$	1	1	1	1	1	1	2	1	1	2	2	1	1	1
$p \geq 0.95$	1	1	3	1	2	1	2	1	1	2	4	2	2	1
<i>2b. Capital ratio, Household spread, Household lending, Production, SovCISS, Household loan losses</i>														
$p \geq 0.99$	3	1	1	1	1	2	1	1	1	1	2	1	1	1
$p \geq 0.95$	3	1	3	1	1	2	2	2	1	1	2	1	2	1
<i>2c. Capital ratio, Aggregate spread, Aggregate lending, Production, SovCISS, Aggregate loan losses</i>														
$p \geq 0.99$	1	1	1	1	1	1	2	1	1	2	2	2	1	1
$p \geq 0.95$	2	1	3	1	2	1	2	1	1	2	2	2	3	1

Loan loss data is available only for Euro Area countries so this variable is omitted for DK, GB and SE.

The data is based on 15,000 Monte Carlo draws of the hierarchical Bayesian SVAR model with t-distributed error terms. The estimation is performed independently for each country.

**Table 5. Bank capital shocks (instantaneous with 4 sign relations).** Table shows the number of shocks (summed over all countries) that (instantaneously) satisfy all the four hypothesized sign-relations (indicated by +/- at the top part of the table) of a bank capital shock with probability  $p$  higher than 0.25, 0.50, 0.70 or 0.90.

	Capital tightening	Profitability shock
Sign relations:		
<i>Capital ratio</i>	+	+
<i>Lending spread</i>	+	-
<i>Lending growth</i>	-	+
<i>Production</i>	-	+
	(1)	(2)
<i>1a. Capital ratio, Corporate spread, Corporate lending, Production</i>		
$p \geq 0.25$	15	10
$p \geq 0.50$	5	4
$p \geq 0.70$	1	1
$p \geq 0.90$	0	0
<i>1b. Capital ratio, Household spread, Household lending, Production</i>		
$p \geq 0.25$	18	11
$p \geq 0.50$	6	4
$p \geq 0.70$	0	2
$p \geq 0.90$	0	0
<i>1c. Capital ratio, Aggregate spread, Aggregate lending, Production</i>		
$p \geq 0.25$	13	9
$p \geq 0.50$	6	6
$p \geq 0.70$	4	1
$p \geq 0.90$	0	0
<i>2a. Capital ratio, Corporate spread, Corporate lending, Production, SovCISS, Corporate loan losses*</i>		
$p \geq 0.25$	18	13
$p \geq 0.50$	2	4
$p \geq 0.70$	1	0
$p \geq 0.90$	0	0
<i>2b. Capital ratio, Household spread, Household lending, Production, SovCISS, Household loan losses*</i>		
$p \geq 0.25$	17	12
$p \geq 0.50$	7	3
$p \geq 0.70$	1	2
$p \geq 0.90$	0	0
<i>2c. Capital ratio, Aggregate spread, Aggregate lending, Production, SovCISS, Aggregate loan losses*</i>		
$p \geq 0.25$	19	13
$p \geq 0.50$	6	6
$p \geq 0.70$	2	1
$p \geq 0.90$	0	0

Number of countries is 14.

**Table 6. Bank capital shocks (instantaneous impact).** Table shows the number of shocks (summed over all countries) that on impact satisfy a set of sign-relations (indicated by +/- at the top part of the table) related to bank capital shock with probability  $p$  higher than 0.25, 0.50, 0.70 or 0.90.

	Capital tightening (1–6)					Profitability shock (7–12)						
Sign relations:												
<i>Capital ratio</i>	+	+	+	+	+	+	+	+	+	+	+	+
<i>Lending spread</i>	+		+	+		+	–		–	–		–
<i>Lending growth</i>		–	–		–	–		+	+		+	+
<i>Production</i>				–	–	–				+	+	+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<i>1a. Capital ratio, Corporate spread, Corporate lending, Production</i>												
$p \geq 0.25$	45	50	20	18	18	15	46	43	20	20	23	10
$p \geq 0.50$	29	32	6	6	7	5	27	24	9	8	8	4
$p \geq 0.70$	13	14	2	4	4	1	16	10	5	2	2	1
$p \geq 0.90$	6	6	1	2	0	0	6	2	1	1	0	0
<i>1b. Capital ratio, Household spread, Household lending, Production</i>												
$p \geq 0.25$	49	47	20	29	25	18	42	50	24	17	26	11
$p \geq 0.50$	36	21	9	12	9	6	20	35	7	9	13	4
$p \geq 0.70$	18	8	2	5	2	0	9	14	5	4	7	2
$p \geq 0.90$	5	2	1	1	0	0	3	2	1	2	1	0
<i>1c. Capital ratio, Aggregate spread, Aggregate lending, Production</i>												
$p \geq 0.25$	48	47	23	18	19	13	41	42	18	17	22	9
$p \geq 0.50$	30	30	12	7	9	6	26	26	13	8	13	6
$p \geq 0.70$	19	16	6	5	6	4	9	13	4	3	4	1
$p \geq 0.90$	6	6	2	3	3	0	6	2	2	2	1	0
<i>2a. Capital ratio, Corporate spread, Corporate lending, Production, SovCISS, Corporate loan losses</i>												
$p \geq 0.25$	68	70	29	27	37	18	70	67	29	31	34	13
$p \geq 0.50$	45	48	9	11	13	2	36	33	13	12	9	4
$p \geq 0.70$	17	20	4	4	4	1	18	13	4	4	2	0
$p \geq 0.90$	7	4	1	1	1	0	8	2	1	0	1	0
<i>2b. Capital ratio, Household spread, Household lending, Production, SovCISS, Household loan losses</i>												
$p \geq 0.25$	71	69	30	34	30	17	63	76	32	26	39	12
$p \geq 0.50$	49	31	15	18	10	7	32	50	10	9	13	3
$p \geq 0.70$	22	10	4	7	3	1	14	14	4	4	5	2
$p \geq 0.90$	5	1	0	1	0	0	5	2	0	2	1	0
<i>2c. Capital ratio, Aggregate spread, Aggregate lending, Production, SovCISS, Aggregate loan losses</i>												
$p \geq 0.25$	70	75	37	29	31	19	65	69	34	32	36	13
$p \geq 0.50$	47	42	13	8	12	6	34	39	12	10	11	6
$p \geq 0.70$	18	19	3	4	4	2	15	11	4	2	2	1
$p \geq 0.90$	7	4	1	1	0	0	6	2	1	0	0	0

Number of countries is 14.

**Table 7. Bank capital shocks (gradual impact).** Table shows the number of shocks (summed over all countries) that satisfy a set of sign-relations (indicated by +/- at the top part of the table) related to bank capital shock with probability  $p$  higher than 0.25, 0.50, 0.70 or 0.90. The sign relation for capital ratio must hold on impact and other sign relations must hold at 12 month lag.

	Capital tightening (1–6)						Profitability shock (7–12)					
Sign relations:												
<i>Capital ratio</i>	+	+	+	+	+	–	+	+	+	+	+	+
<i>Lending spread</i>	+		+	+		–	–		–	–		–
<i>Lending growth</i>		–	–		–	+		+	+		+	+
<i>Production</i>				–	–	+				+	+	+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<i>1a. Capital ratio, Corporate spread, Corporate lending, Production</i>												
$p \geq 0.25$	47	44	15	25	24	19	48	44	34	38	34	26
$p \geq 0.50$	26	27	8	9	11	4	30	29	14	21	13	10
$p \geq 0.70$	11	15	5	3	6	2	11	12	7	7	9	6
$p \geq 0.90$	4	4	1	1	1	1	4	2	2	3	2	2
<i>1b. Capital ratio, Household spread, Household lending, Production</i>												
$p \geq 0.25$	45	43	11	16	17	12	49	54	33	40	40	29
$p \geq 0.50$	20	19	4	9	4	3	36	37	14	16	20	9
$p \geq 0.70$	9	2	1	1	0	0	13	17	6	7	11	5
$p \geq 0.90$	4	1	1	0	0	0	4	6	2	2	4	1
<i>1c. Capital ratio, Aggregate spread, Aggregate lending, Production</i>												
$p \geq 0.25$	43	40	14	26	21	22	47	45	38	43	36	31
$p \geq 0.50$	25	23	7	11	10	6	31	33	18	19	18	14
$p \geq 0.70$	10	12	4	3	3	3	15	17	10	11	10	7
$p \geq 0.90$	4	5	1	1	2	1	8	5	4	4	3	2
<i>2a. Capital ratio, Corporate spread, Corporate lending, Production, SovCISS, Corporate loan losses*</i>												
$p \geq 0.25$	67	65	30	42	41	27	67	66	52	53	50	36
$p \geq 0.50$	40	40	14	13	19	10	41	41	20	26	20	12
$p \geq 0.70$	18	16	6	2	6	3	19	21	9	10	8	5
$p \geq 0.90$	6	4	2	2	1	1	8	5	3	4	2	2
<i>2b. Capital ratio, Household spread, Household lending, Production, SovCISS, Household loan losses*</i>												
$p \geq 0.25$	67	65	32	32	30	22	65	73	39	47	51	32
$p \geq 0.50$	42	28	8	8	8	4	39	53	20	23	29	16
$p \geq 0.70$	20	9	1	2	1	0	17	24	8	10	12	7
$p \geq 0.90$	5	0	0	1	0	0	6	6	3	3	4	2
<i>2c. Capital ratio, Aggregate spread, Aggregate lending, Production, SovCISS, Aggregate loan losses*</i>												
$p \geq 0.25$	62	61	29	32	34	27	70	68	52	52	49	38
$p \geq 0.50$	36	33	9	10	11	8	45	48	28	28	25	21
$p \geq 0.70$	17	13	5	3	3	5	23	22	15	13	12	7
$p \geq 0.90$	5	3	1	1	0	0	7	7	3	6	5	3

Number of countries is 14.

**Table 8. Posterior estimates for degrees of freedom parameter (substitution shocks).** The error process is assumed to follow  $t$ -distribution. Table shows the posterior estimates of the degree of freedom parameter  $\lambda_k$  of each error component for specifications 3–6.

**a) Substitution between corporate and household borrowers**

	EA	DE	FR	GB	IT	ES	FI	SE	DK	AT	BE	NL	PT	IE
$T$	162	161	161	161	161	161	161	135	161	161	161	161	161	93
<i>3. Capital ratio, Relative firm lending spread, Relative firm lending growth, Product</i>														
$\lambda_{1,p50}$	<b>6.6</b>	<b>3.3</b>	<b>4.2</b>	<b>8.9</b>	<b>2.3</b>	<b>2.6</b>	<b>3.3</b>	<b>4.3</b>	<b>8.5</b>	<b>2.5</b>	<b>2.4</b>	<b>2.8</b>	<b>2.5</b>	<b>2.4</b>
$\lambda_{1,p10}$	3.6	2.4	2.7	5.0	2.1	2.1	2.4	2.6	5.0	2.1	2.1	2.2	2.1	2.1
$\lambda_{1,p90}$	12.7	5.1	8.6	16.8	2.9	3.5	4.8	8.5	15.9	3.2	3.1	3.9	3.3	3.1
$\lambda_{2,p50}$	<b>3.5</b>	<b>4.7</b>	<b>3.5</b>	<b>4.4</b>	<b>4.3</b>	<b>2.8</b>	<b>6.3</b>	<b>5.1</b>	<b>9.2</b>	<b>4.8</b>	<b>2.9</b>	<b>5.8</b>	<b>7.7</b>	<b>5.7</b>
$\lambda_{2,p10}$	2.5	3.0	2.5	2.9	2.7	2.2	3.7	3.1	5.0	3.1	2.2	3.1	4.2	2.9
$\lambda_{2,p90}$	5.5	8.5	5.0	7.4	8.0	4.3	12.3	9.7	17.8	8.1	4.4	13.1	15.1	12.2
$\lambda_{3,p50}$	<b>4.8</b>	<b>4.5</b>	<b>2.8</b>	<b>2.0</b>	<b>7.6</b>	<b>6.5</b>	<b>3.0</b>	<b>2.1</b>	<b>2.2</b>	<b>3.2</b>	<b>2.9</b>	<b>6.9</b>	<b>7.7</b>	<b>7.8</b>
$\lambda_{3,p10}$	3.0	2.9	2.2	2.0	4.4	3.9	2.3	2.0	2.0	2.3	2.2	3.7	4.1	3.9
$\lambda_{3,p90}$	9.8	7.9	4.1	2.1	14.5	12.8	4.5	2.4	2.6	4.8	4.1	14.8	16.2	16.3
$\lambda_{4,p50}$	<b>7.3</b>	<b>8.5</b>	<b>10.7</b>	<b>3.9</b>	<b>8.2</b>	<b>3.3</b>	<b>4.7</b>	<b>12.0</b>	<b>8.4</b>	<b>7.9</b>	<b>7.4</b>	<b>10.5</b>	<b>7.8</b>	<b>7.2</b>
$\lambda_{4,p10}$	4.1	4.9	5.5	2.5	4.8	2.4	3.0	6.4	4.7	4.5	4.3	5.6	4.3	3.7
$\lambda_{4,p90}$	14.5	16.0	19.8	7.0	15.2	5.1	9.4	21.7	15.9	15.2	13.9	19.6	15.6	15.0
<i>4. Capital ratio, Relative firm lending spread, Relative firm lending growth, Production, SovCISS, Corporate loan losses</i>														
$\lambda_{1,p50}$	<b>4.6</b>	<b>3.6</b>	<b>3.5</b>	<b>9.5</b>	<b>2.3</b>	<b>2.5</b>	<b>3.0</b>	<b>4.0</b>	<b>8.5</b>	<b>2.4</b>	<b>2.4</b>	<b>2.5</b>	<b>2.4</b>	<b>2.3</b>
$\lambda_{1,p10}$	2.8	2.5	2.4	5.2	2.1	2.1	2.3	2.6	4.8	2.1	2.1	2.1	2.1	2.1
$\lambda_{1,p90}$	9.6	5.9	6.2	18.7	2.9	3.3	4.3	7.4	15.8	3.1	3.1	3.3	3.1	3.0
$\lambda_{2,p50}$	<b>3.9</b>	<b>4.9</b>	<b>3.8</b>	<b>4.7</b>	<b>3.6</b>	<b>2.9</b>	<b>7.4</b>	<b>4.9</b>	<b>8.0</b>	<b>3.9</b>	<b>3.1</b>	<b>7.3</b>	<b>5.1</b>	<b>5.9</b>
$\lambda_{2,p10}$	2.6	3.1	2.8	3.0	2.5	2.2	4.4	3.0	4.5	2.6	2.2	3.9	2.9	3.0
$\lambda_{2,p90}$	6.7	9.0	5.7	8.6	7.0	4.5	13.6	9.6	15.8	6.2	5.7	15.2	11.5	13.2
$\lambda_{3,p50}$	<b>5.0</b>	<b>3.9</b>	<b>2.7</b>	<b>2.0</b>	<b>7.4</b>	<b>8.2</b>	<b>3.1</b>	<b>2.1</b>	<b>2.2</b>	<b>2.9</b>	<b>3.2</b>	<b>6.7</b>	<b>6.6</b>	<b>6.6</b>
$\lambda_{3,p10}$	2.9	2.6	2.2	2.0	4.3	4.6	2.3	2.0	2.0	2.2	2.3	3.7	3.7	3.3
$\lambda_{3,p90}$	11.1	6.2	3.8	2.1	13.8	16.1	4.8	2.4	2.6	4.2	5.3	13.4	13.7	14.7
$\lambda_{4,p50}$	<b>4.9</b>	<b>8.1</b>	<b>9.6</b>	<b>4.6</b>	<b>8.0</b>	<b>2.8</b>	<b>6.0</b>	<b>12.3</b>	<b>8.2</b>	<b>7.4</b>	<b>5.9</b>	<b>8.4</b>	<b>8.8</b>	<b>5.1</b>
$\lambda_{4,p10}$	2.6	4.6	5.2	2.9	4.6	2.2	3.5	6.6	4.7	4.2	3.6	4.5	4.8	2.6
$\lambda_{4,p90}$	10.9	15.5	17.8	8.9	16.4	4.0	11.3	22.3	15.8	14.7	10.8	15.7	16.3	12.2
$\lambda_{5,p50}$	<b>3.0</b>	<b>2.2</b>	<b>2.3</b>	<b>2.3</b>	<b>2.4</b>	<b>2.4</b>	<b>2.3</b>	<b>2.5</b>	<b>2.6</b>	<b>2.2</b>	<b>2.2</b>	<b>2.5</b>	<b>4.8</b>	<b>2.4</b>
$\lambda_{5,p10}$	2.2	2.0	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.0	2.0	2.1	2.9	2.1
$\lambda_{5,p90}$	5.5	2.8	2.9	3.0	3.2	3.1	2.9	3.4	3.4	2.6	2.5	3.4	9.3	3.2
$\lambda_{6,p50}$	<b>2.1</b>	<b>2.8</b>	<b>2.3</b>	-	<b>2.1</b>	<b>2.0</b>	<b>2.1</b>	-	-	<b>2.3</b>	<b>2.2</b>	<b>2.2</b>	<b>2.1</b>	<b>2.0</b>
$\lambda_{6,p10}$	2.0	2.2	2.0	-	2.0	2.0	2.0	-	-	2.0	2.0	2.0	2.0	2.0
$\lambda_{6,p90}$	2.3	4.4	2.8	-	2.2	2.1	2.4	-	-	2.8	2.6	2.5	2.3	2.1



**b) Substitution between corporate bank loans and security issuance**

	EA	DE	FR	IT	ES	FI	AT	BE	NL	PT
<i>T</i>	162	164	163	163	163	162	163	163	163	164
<i>5. Capital ratio, Lending relative to bond markets,</i>										
<i>Production</i>										
$\lambda_{1,p50}$	<b>4.2</b>	<b>3.3</b>	<b>3.6</b>	<b>2.3</b>	<b>2.8</b>	<b>3.1</b>	<b>2.5</b>	<b>2.6</b>	<b>3.0</b>	<b>2.5</b>
$\lambda_{1,p10}$	2.5	2.4	2.5	2.1	2.2	2.3	2.1	2.1	2.3	2.1
$\lambda_{1,p90}$	9.0	5.1	6.0	2.9	3.7	4.5	3.2	3.4	4.2	3.1
$\lambda_{2,p50}$	<b>3.4</b>	<b>2.7</b>	<b>4.6</b>	<b>2.6</b>	<b>3.3</b>	<b>2.6</b>	<b>2.5</b>	<b>2.5</b>	<b>2.6</b>	<b>2.4</b>
$\lambda_{2,p10}$	2.4	2.2	2.8	2.1	2.3	2.1	2.1	2.1	2.1	2.1
$\lambda_{2,p90}$	6.1	3.6	9.4	3.4	5.7	3.5	3.2	3.4	3.5	3.0
$\lambda_{3,p50}$	<b>9.3</b>	<b>7.7</b>	<b>9.6</b>	<b>9.0</b>	<b>3.4</b>	<b>5.2</b>	<b>8.7</b>	<b>6.3</b>	<b>11.2</b>	<b>7.1</b>
$\lambda_{3,p10}$	5.4	4.7	5.0	5.0	2.4	3.2	5.0	3.9	6.2	4.3
$\lambda_{3,p90}$	17.0	13.8	18.6	17.4	4.9	9.4	16.9	11.8	20.2	13.6
<i>6. Capital ratio, Lending relative to bond markets,</i>										
<i>Production, SovCISS, Corporate loan losses</i>										
$\lambda_{1,p50}$	<b>4.0</b>	<b>3.4</b>	<b>3.4</b>	<b>2.3</b>	<b>2.6</b>	<b>2.9</b>	<b>2.5</b>	<b>2.4</b>	<b>2.5</b>	<b>2.5</b>
$\lambda_{1,p10}$	2.6	2.4	2.4	2.1	2.1	2.2	2.1	2.1	2.1	2.1
$\lambda_{1,p90}$	7.3	5.6	5.4	2.9	3.3	4.2	3.2	3.1	3.5	3.2
$\lambda_{2,p50}$	<b>4.0</b>	<b>2.6</b>	<b>4.4</b>	<b>2.4</b>	<b>3.4</b>	<b>2.7</b>	<b>2.4</b>	<b>2.4</b>	<b>2.6</b>	<b>2.3</b>
$\lambda_{2,p10}$	2.6	2.2	2.6	2.1	2.3	2.1	2.1	2.1	2.1	2.1
$\lambda_{2,p90}$	7.2	3.5	9.3	3.2	6.0	3.9	3.0	3.2	3.5	2.9
$\lambda_{3,p50}$	<b>7.2</b>	<b>7.7</b>	<b>11.1</b>	<b>8.4</b>	<b>2.6</b>	<b>6.2</b>	<b>9.5</b>	<b>5.7</b>	<b>10.5</b>	<b>7.5</b>
$\lambda_{3,p10}$	3.3	4.6	6.0	4.7	2.1	3.7	5.2	3.5	5.9	4.3
$\lambda_{3,p90}$	16.1	14.1	20.3	15.8	3.7	11.5	18.4	11.0	19.8	14.5
$\lambda_{4,p50}$	<b>3.1</b>	<b>2.2</b>	<b>2.2</b>	<b>2.5</b>	<b>2.5</b>	<b>2.3</b>	<b>2.2</b>	<b>2.1</b>	<b>2.4</b>	<b>3.1</b>
$\lambda_{4,p10}$	2.2	2.0	2.0	2.1	2.1	2.1	2.0	2.0	2.1	2.2
$\lambda_{4,p90}$	6.9	2.7	2.7	3.3	3.5	2.9	2.6	2.5	3.1	5.3
$\lambda_{5,p50}$	<b>2.1</b>	<b>2.7</b>	<b>2.3</b>	<b>2.1</b>	<b>2.0</b>	<b>2.1</b>	<b>2.2</b>	<b>2.2</b>	<b>2.2</b>	<b>2.1</b>
$\lambda_{5,p10}$	2.0	2.1	2.1	2.0	2.0	2.0	2.0	2.0	2.0	2.0
$\lambda_{5,p90}$	2.4	3.9	3.0	2.2	2.1	2.4	2.8	2.6	2.5	2.3

For Great Britain, Sweden, Denmark, and Ireland, the bond data was either not available or insufficient in length.

**Table 9. Substitution due to bank capital shocks.** Table shows the number of shocks that satisfy a set of sign-relations (indicated by +/- at the top part of the table) related to bank capital shock with probability  $p$  higher than 0.25, 0.50, 0.70 or 0.90. The sign relations must hold either on impact or at 12 month lag as indicated in the subheaders.

**a) Substitution between corporate and household borrowers**

	Capital tightening (1–6)						Profitability shock (7–12)					
Sign relations:												
<i>Capital ratio</i>	+	+	+	+	+	+	+	+	+	+	+	+
<i>Relative firm lending spread</i>	+		+	+		+	–		–	–		–
<i>Relative firm lending growth</i>		–	–		–	–		+	+		+	+
<i>Production</i>				–	–	–				+	+	+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<b>Instantaneous response for all variables</b>												
<i>3. Capital ratio, Relative firm lending spread, Relative firm lending growth, Production</i>												
$p \geq 0.25$	42	50	13	14	19	12	48	42	24	17	18	7
$p \geq 0.50$	25	33	7	7	6	3	31	23	7	5	6	2
$p \geq 0.70$	13	19	2	4	3	0	16	8	3	5	3	1
$p \geq 0.90$	3	5	1	0	1	0	4	2	0	1	1	0
<i>4. Capital ratio, Relative firm lending spread, Relative firm lending growth, Production, SovCISS, Corporate loan losses</i>												
$p \geq 0.25$	67	72	21	24	31	15	70	63	36	26	24	11
$p \geq 0.50$	36	43	10	6	10	4	45	38	11	10	9	1
$p \geq 0.70$	15	24	5	1	4	0	19	10	1	2	3	0
$p \geq 0.90$	3	6	1	0	1	0	5	2	0	0	1	0
<b>Instantaneous response for Capital ratio, 12 month response for other variables</b>												
<i>5. Capital ratio, Lending relative to bond markets, Production</i>												
$p \geq 0.25$	46	49	9	19	25	6	48	41	17	20	23	6
$p \geq 0.50$	28	34	2	6	11	2	28	22	4	8	9	1
$p \geq 0.70$	11	18	0	1	6	1	11	7	0	2	3	0
$p \geq 0.90$	3	4	0	0	2	0	1	3	0	1	1	0
<i>6. Capital ratio, Lending relative to bond markets, Production, SovCISS, Corporate loan losses</i>												
$p \geq 0.25$	69	69	23	36	40	7	71	62	24	32	37	10
$p \geq 0.50$	40	46	8	16	21	0	41	35	6	15	15	2
$p \geq 0.70$	15	21	2	3	8	0	16	18	1	6	4	0
$p \geq 0.90$	6	8	0	1	0	0	3	3	0	1	0	0

Number of countries is 14.

**b) Substitution between corporate bank loans and security issuance**

	Capital tightening (1–2)		Profitability shock (3–4)	
Sign relations:				
<i>Capital ratio</i>	+	+	+	+
<i>Lending relative to bond markets</i>	–	–	+	+
<i>Production</i>		–		+
	(1)	(2)	(3)	(4)
<b>Instantaneous response for all variables</b>				
5. <i>Capital ratio, Lending relative to bond markets, Production</i>				
$p \geq 0.25$	26	8	21	10
$p \geq 0.50$	18	5	12	7
$p \geq 0.70$	10	1	5	1
$p \geq 0.90$	3	1	2	0
6. <i>Capital ratio, Lending relative to bond markets, Production, SovCISS, Corporate loan losses</i>				
$p \geq 0.25$	42	15	42	16
$p \geq 0.50$	31	6	19	6
$p \geq 0.70$	11	4	11	2
$p \geq 0.90$	3	1	2	0
<b>Instantaneous response for Capital ratio, 12 month response for other variables</b>				
5. <i>Capital ratio, Lending relative to bond markets, Production</i>				
$p \geq 0.25$	24	11	21	13
$p \geq 0.50$	16	6	14	6
$p \geq 0.70$	13	3	8	4
$p \geq 0.90$	4	1	4	1
6. <i>Capital ratio, Lending relative to bond markets, Production, SovCISS, Corporate loan losses</i>				
$p \geq 0.25$	37	17	42	28
$p \geq 0.50$	20	7	30	16
$p \geq 0.70$	10	3	16	7
$p \geq 0.90$	4	2	4	2

Number of countries is 10. For Great Britain, Sweden, Denmark, and Ireland, the bond data was either not available or insufficient in length.

**Table 10. Posterior estimates for degrees of freedom parameter (robustness check).** The error process is assumed to follow t-distribution. Table shows the posterior estimates of the degree of freedom parameter  $\lambda_k$  of each error component for specifications 1a and 2a extended with inflation and short rate.

Country	EA	DE	FR	GB	IT	ES	FI	SE	DK	AT	BE	NL	PT	IE
<i>T</i>	162	161	161	161	161	161	161	135	161	161	161	161	161	93
<i>1a. Capital ratio, Corporate spread, Corporate lending, Production, Inflation, Short term interest rate</i>														
<b><math>\lambda_{1,p50}</math></b>	<b>4.6</b>	<b>3.2</b>	<b>4.6</b>	<b>8.9</b>	<b>2.2</b>	<b>2.7</b>	<b>3.6</b>	<b>3.8</b>	<b>9.3</b>	<b>2.4</b>	<b>5.1</b>	<b>2.6</b>	<b>2.5</b>	<b>2.3</b>
$\lambda_{1,p10}$	2.8	2.3	2.8	4.3	2.0	2.2	2.5	2.5	5.0	2.1	3.1	2.1	2.1	2.1
$\lambda_{1,p90}$	9.7	4.9	9.0	17.6	2.8	3.7	5.8	7.1	17.5	3.0	9.3	3.6	3.3	3.0
<b><math>\lambda_{2,p50}</math></b>	<b>3.2</b>	<b>4.1</b>	<b>4.4</b>	<b>4.6</b>	<b>6.8</b>	<b>3.8</b>	<b>6.1</b>	<b>5.3</b>	<b>9.3</b>	<b>2.9</b>	<b>2.3</b>	<b>7.5</b>	<b>9.1</b>	<b>5.9</b>
$\lambda_{2,p10}$	2.3	2.5	2.8	2.9	3.5	2.7	3.6	2.9	4.9	2.2	2.1	3.8	5.0	3.0
$\lambda_{2,p90}$	5.1	8.7	8.2	8.2	14.7	6.1	12.2	10.8	18.5	4.2	2.9	15.3	16.8	13.9
<b><math>\lambda_{3,p50}</math></b>	<b>5.7</b>	<b>4.0</b>	<b>3.4</b>	<b>7.2</b>	<b>5.7</b>	<b>5.0</b>	<b>3.3</b>	<b>2.4</b>	<b>2.5</b>	<b>3.6</b>	<b>3.3</b>	<b>5.5</b>	<b>6.7</b>	<b>8.4</b>
$\lambda_{3,p10}$	3.3	2.6	2.3	3.8	3.4	3.2	2.3	2.1	2.1	2.5	2.3	3.2	3.7	4.0
$\lambda_{3,p90}$	11.6	6.6	6.1	15.5	12.1	8.8	5.4	3.3	3.4	5.6	5.6	11.4	12.9	16.6
<b><math>\lambda_{4,p50}</math></b>	<b>6.8</b>	<b>9.2</b>	<b>10.0</b>	<b>5.4</b>	<b>5.9</b>	<b>2.6</b>	<b>5.2</b>	<b>10.8</b>	<b>7.8</b>	<b>10.6</b>	<b>6.1</b>	<b>9.4</b>	<b>7.5</b>	<b>6.5</b>
$\lambda_{4,p10}$	3.7	5.1	5.4	3.1	3.6	2.1	3.0	5.4	4.3	5.4	3.8	5.2	4.1	3.3
$\lambda_{4,p90}$	13.6	17.1	19.2	10.8	11.3	3.5	10.7	20.2	15.5	20.7	11.4	18.8	14.3	14.1
<b><math>\lambda_{5,p50}</math></b>	<b>6.1</b>	<b>2.9</b>	<b>7.6</b>	<b>5.6</b>	<b>3.3</b>	<b>2.2</b>	<b>7.9</b>	<b>4.7</b>	<b>6.3</b>	<b>7.0</b>	<b>3.9</b>	<b>3.0</b>	<b>2.4</b>	<b>3.2</b>
$\lambda_{5,p10}$	3.4	2.2	4.0	3.3	2.4	2.0	3.5	2.8	3.8	4.0	2.6	2.2	2.1	2.3
$\lambda_{5,p90}$	11.6	4.8	14.7	11.6	4.8	2.5	16.3	10.2	11.4	14.1	7.1	4.6	3.1	5.3
<b><math>\lambda_{6,p50}</math></b>	<b>2.1</b>	-	-	-	-	-	-	-	-	-	-	-	-	-
$\lambda_{6,p10}$	2.0	-	-	-	-	-	-	-	-	-	-	-	-	-
$\lambda_{6,p90}$	2.3	-	-	-	-	-	-	-	-	-	-	-	-	-
<i>2a. Capital ratio, Corporate spread, Corporate lending, Production, SovCIS, Corporate loan losses, Inflation, Short term interest rate</i>														
<b><math>\lambda_{1,p50}</math></b>	<b>4.6</b>	<b>3.3</b>	<b>4.6</b>	<b>8.3</b>	<b>2.3</b>	<b>2.6</b>	<b>3.0</b>	<b>3.6</b>	<b>8.3</b>	<b>2.3</b>	<b>2.2</b>	<b>2.4</b>	<b>2.3</b>	<b>2.3</b>
$\lambda_{1,p10}$	2.8	2.3	2.8	3.7	2.0	2.1	2.2	2.4	4.5	2.1	2.0	2.1	2.1	2.1
$\lambda_{1,p90}$	9.9	5.1	9.5	17.1	2.8	3.5	5.7	6.6	16.1	2.8	2.7	3.2	2.9	2.8
<b><math>\lambda_{2,p50}</math></b>	<b>2.6</b>	<b>3.4</b>	<b>2.3</b>	<b>4.4</b>	<b>4.8</b>	<b>4.6</b>	<b>5.2</b>	<b>5.2</b>	<b>9.5</b>	<b>2.5</b>	<b>5.3</b>	<b>6.1</b>	<b>5.3</b>	<b>3.5</b>
$\lambda_{2,p10}$	2.1	2.3	2.1	2.8	3.1	2.9	2.9	3.0	5.1	2.1	2.9	3.2	3.0	2.3
$\lambda_{2,p90}$	3.9	7.0	2.9	8.2	8.6	8.0	10.5	10.7	18.9	3.5	12.0	14.0	11.1	7.0
<b><math>\lambda_{3,p50}</math></b>	<b>5.2</b>	<b>4.2</b>	<b>3.9</b>	<b>6.7</b>	<b>5.9</b>	<b>8.7</b>	<b>3.5</b>	<b>2.4</b>	<b>2.5</b>	<b>3.4</b>	<b>3.4</b>	<b>5.8</b>	<b>6.4</b>	<b>7.0</b>
$\lambda_{3,p10}$	2.7	2.8	2.5	3.5	3.5	4.9	2.4	2.1	2.1	2.4	2.3	3.3	3.6	3.3
$\lambda_{3,p90}$	10.8	7.0	8.1	14.6	11.7	16.1	6.8	3.4	3.4	5.2	5.8	12.1	13.2	15.3
<b><math>\lambda_{4,p50}</math></b>	<b>6.1</b>	<b>8.3</b>	<b>8.5</b>	<b>5.7</b>	<b>5.6</b>	<b>2.6</b>	<b>5.7</b>	<b>10.5</b>	<b>7.5</b>	<b>9.1</b>	<b>5.1</b>	<b>7.6</b>	<b>7.2</b>	<b>7.5</b>
$\lambda_{4,p10}$	3.2	4.6	4.3	3.0	3.5	2.1	3.3	4.9	4.1	4.7	3.2	3.5	4.0	3.7
$\lambda_{4,p90}$	12.2	16.0	16.7	12.6	10.5	3.7	11.4	20.8	15.0	17.7	9.2	16.0	14.2	15.6
<b><math>\lambda_{5,p50}</math></b>	<b>3.3</b>	<b>2.2</b>	<b>2.2</b>	<b>2.6</b>	<b>2.4</b>	<b>2.4</b>	<b>2.3</b>	<b>2.3</b>	<b>2.4</b>	<b>2.2</b>	<b>2.1</b>	<b>2.5</b>	<b>4.0</b>	<b>2.5</b>
$\lambda_{5,p10}$	2.2	2.0	2.0	2.1	2.1	2.1	2.0	2.0	2.1	2.0	2.0	2.1	2.6	2.1
$\lambda_{5,p90}$	6.8	2.6	2.7	3.7	3.3	3.0	2.8	2.9	3.2	2.5	2.5	3.4	7.7	3.8
<b><math>\lambda_{6,p50}</math></b>	<b>2.1</b>	<b>2.6</b>	<b>4.5</b>	<b>5.3</b>	<b>2.1</b>	<b>2.0</b>	<b>2.1</b>	<b>4.9</b>	<b>6.0</b>	<b>2.3</b>	<b>2.2</b>	<b>2.2</b>	<b>2.1</b>	<b>2.1</b>
$\lambda_{6,p10}$	2.0	2.1	2.7	3.2	2.0	2.0	2.0	2.9	3.5	2.0	2.0	2.0	2.0	2.0
$\lambda_{6,p90}$	2.3	4.0	10.3	10.4	2.2	2.1	2.3	10.5	12.0	2.9	2.7	2.5	2.2	2.2
<b><math>\lambda_{7,p50}</math></b>	<b>5.4</b>	<b>3.5</b>	<b>5.3</b>	-	<b>3.1</b>	<b>2.2</b>	<b>7.9</b>	-	-	<b>6.4</b>	<b>3.9</b>	<b>3.0</b>	<b>2.3</b>	<b>4.8</b>
$\lambda_{7,p10}$	3.1	2.3	3.2	-	2.3	2.0	3.6	-	-	3.6	2.5	2.2	2.1	2.5
$\lambda_{7,p90}$	12.0	6.3	10.2	-	4.5	2.5	17.0	-	-	13.6	7.5	5.7	3.0	12.7
<b><math>\lambda_{8,p50}</math></b>	<b>2.1</b>	-	-	-	-	-	-	-	-	-	-	-	-	-
$\lambda_{8,p10}$	2.0	-	-	-	-	-	-	-	-	-	-	-	-	-
$\lambda_{8,p90}$	2.4	-	-	-	-	-	-	-	-	-	-	-	-	-

*T* is the number of observations.

**Table 11 Bank capital shocks (instantaneous, robustness check)** Table shows the number of shocks that satisfy a set of instantaneous sign-relations (indicated by +/- at the top part of the table) related to bank capital shock with probability  $p$  higher than 0.25, 0.50, 0.70 or 0.90.

	Capital tightening (1–6)						Profitability shock (7–12)					
Sign relations:												
<i>Capital ratio</i>	+	+	+	+	+	–	+	+	+	+	+	+
<i>Lending spread</i>	+		+	+		–	–		–	–		–
<i>Lending growth</i>		–	–		–	+		+	+		+	+
<i>Production</i>				–	–	+				+	+	+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<i>1a. Capital ratio, Corporate spread, Corporate lending, Production, Inflation, Short-term interest rate</i>												
$p \geq 0.25$	70	75	23	28	25	21	73	74	31	36	38	19
$p \geq 0.50$	50	53	5	7	10	7	34	31	10	14	8	5
$p \geq 0.70$	12	13	2	4	3	0	17	11	6	5	3	1
$p \geq 0.90$	4	2	1	0	0	0	6	1	1	2	1	1
<i>1b. Capital ratio, Household spread, Household lending, Production, Inflation, Short-term interest rate</i>												
$p \geq 0.25$	72	72	31	31	27	23	71	72	37	38	33	21
$p \geq 0.50$	47	41	12	13	8	5	37	43	13	14	14	5
$p \geq 0.70$	18	16	5	2	2	0	15	16	6	6	6	3
$p \geq 0.90$	6	2	0	0	0	0	4	4	2	2	1	1
<i>1c. Capital ratio, Aggregate spread, Aggregate lending, Production, Inflation, Short-term interest rate</i>												
$p \geq 0.25$	70	75	36	25	26	18	74	74	32	39	35	18
$p \geq 0.50$	45	42	9	10	8	4	39	42	14	13	15	8
$p \geq 0.70$	15	15	3	2	3	0	19	12	6	6	5	3
$p \geq 0.90$	6	3	1	0	0	0	8	2	2	2	1	1
<i>2a. Capital ratio, Corporate spread, Corporate lending, Production, SovCISS, Corporate loan losses, Inflation, Short-term interest rate</i>												
$p \geq 0.25$	89	100	37	38	35	21	97	93	43	44	45	18
$p \geq 0.50$	60	71	8	10	13	9	49	38	14	14	11	7
$p \geq 0.70$	18	20	2	3	4	0	24	13	4	7	2	0
$p \geq 0.90$	6	2	1	0	0	0	7	1	0	1	0	0
<i>2b. Capital ratio, Household spread, Household lending, Production, SovCISS, Household loan losses, Inflation, Short-term interest rate</i>												
$p \geq 0.25$	95	94	48	36	34	23	91	94	43	42	45	18
$p \geq 0.50$	60	51	12	13	12	4	49	58	14	12	21	5
$p \geq 0.70$	23	18	3	4	3	2	18	19	5	5	7	3
$p \geq 0.90$	5	2	0	0	0	0	6	5	3	3	3	2
<i>2c. Capital ratio, Aggregate spread, Aggregate lending, Production, SovCISS, Aggregate loan losses, Inflation, Short-term interest rate</i>												
$p \geq 0.25$	88	98	43	38	42	21	97	94	45	39	47	19
$p \geq 0.50$	64	55	12	11	11	4	45	54	14	13	14	6
$p \geq 0.70$	17	17	2	1	4	0	25	14	7	6	6	3
$p \geq 0.90$	4	3	1	0	0	0	6	2	1	0	0	0

**Table 12. Posterior estimates for degrees of freedom parameter (substitution shocks, robustness check).** The error process is assumed to follow  $t$ -distribution. Table shows the posterior estimates of the degree of freedom parameter  $\lambda_k$  of each error component for specifications 3–6.

### a) Substitution between corporate and household borrowers

Country	EA	DE	FR	GB	IT	ES	FI	SE	DK	AT	BE	NL	PT	IE
<i>T</i>	162	161	161	161	161	161	161	135	161	161	161	161	161	93
<i>3. Capital ratio, Relative firm lending spread, Relative firm lending growth, Production, Inflation, Short term interest rate</i>														
$\lambda_{1,p50}$	<b>5.0</b>	<b>3.0</b>	<b>4.3</b>	<b>9.3</b>	<b>2.2</b>	<b>2.5</b>	<b>3.5</b>	<b>3.7</b>	<b>8.2</b>	<b>2.4</b>	<b>2.3</b>	<b>2.6</b>	<b>2.6</b>	<b>2.3</b>
$\lambda_{1,p10}$	3.0	2.2	2.7	4.9	2.0	2.1	2.4	2.5	4.6	2.1	2.1	2.1	2.2	2.1
$\lambda_{1,p90}$	9.7	4.6	8.6	17.9	2.8	3.3	5.6	6.4	15.8	3.0	2.9	3.7	3.5	2.9
$\lambda_{2,p50}$	<b>2.1</b>	<b>5.7</b>	<b>3.7</b>	<b>5.6</b>	<b>4.6</b>	<b>3.3</b>	<b>6.2</b>	<b>6.0</b>	<b>8.1</b>	<b>4.9</b>	<b>4.6</b>	<b>7.8</b>	<b>8.1</b>	<b>4.5</b>
$\lambda_{2,p10}$	2.0	3.2	2.7	3.3	2.7	2.3	3.3	3.3	4.6	3.1	2.8	4.0	4.2	2.4
$\lambda_{2,p90}$	2.3	11.2	5.5	10.8	9.0	5.7	13.7	11.6	15.1	9.0	9.8	15.3	15.6	10.1
$\lambda_{3,p50}$	<b>7.3</b>	<b>4.6</b>	<b>2.6</b>	<b>2.0</b>	<b>7.1</b>	<b>6.4</b>	<b>3.1</b>	<b>2.1</b>	<b>2.2</b>	<b>2.7</b>	<b>3.1</b>	<b>5.5</b>	<b>7.9</b>	<b>7.2</b>
$\lambda_{3,p10}$	3.8	2.8	2.1	2.0	4.0	3.7	2.3	2.0	2.0	2.2	2.3	3.1	4.4	3.5
$\lambda_{3,p90}$	14.8	9.7	3.7	2.1	13.9	12.8	4.7	2.4	2.5	3.9	4.8	10.8	14.3	15.7
$\lambda_{4,p50}$	<b>6.2</b>	<b>8.6</b>	<b>10.0</b>	<b>4.5</b>	<b>8.2</b>	<b>2.9</b>	<b>5.8</b>	<b>10.8</b>	<b>8.1</b>	<b>10.2</b>	<b>6.8</b>	<b>9.4</b>	<b>7.3</b>	<b>7.1</b>
$\lambda_{4,p10}$	3.5	4.7	5.4	2.7	4.5	2.2	3.3	5.6	4.4	5.4	4.2	5.1	4.1	3.4
$\lambda_{4,p90}$	11.9	16.1	19.1	9.2	15.2	4.1	12.1	20.5	16.0	20.1	12.3	17.9	14.3	15.4
$\lambda_{5,p50}$	<b>5.8</b>	<b>3.0</b>	<b>5.8</b>	<b>5.2</b>	<b>3.0</b>	<b>2.1</b>	<b>8.6</b>	<b>3.7</b>	<b>6.3</b>	<b>6.9</b>	<b>6.7</b>	<b>3.0</b>	<b>2.5</b>	<b>4.6</b>
$\lambda_{5,p10}$	3.2	2.2	3.3	3.3	2.3	2.0	4.1	2.4	3.9	3.8	3.5	2.3	2.1	2.7
$\lambda_{5,p90}$	12.3	5.1	12.0	9.2	4.2	2.5	17.6	6.9	11.7	14.2	13.7	4.6	3.2	9.4
$\lambda_{6,p50}$	<b>4.4</b>	-	-	-	-	-	-	-	-	-	-	-	-	-
$\lambda_{6,p10}$	2.8	-	-	-	-	-	-	-	-	-	-	-	-	-
$\lambda_{6,p90}$	10.6	-	-	-	-	-	-	-	-	-	-	-	-	-
<i>4. Capital ratio, Relative firm lending spread, Relative firm lending growth, Production, SovCISS, Corporate loan losses, Inflation, Short term interest rate</i>														
$\lambda_{1,p50}$	<b>4.2</b>	<b>3.1</b>	<b>4.1</b>	<b>3.7</b>	<b>2.3</b>	<b>2.4</b>	<b>3.0</b>	<b>3.4</b>	<b>7.9</b>	<b>2.3</b>	<b>2.3</b>	<b>2.4</b>	<b>2.4</b>	<b>2.3</b>
$\lambda_{1,p10}$	2.6	2.3	2.7	2.1	2.0	2.1	2.2	2.4	4.3	2.1	2.1	2.1	2.1	2.1
$\lambda_{1,p90}$	8.4	5.0	7.5	15.3	2.9	3.1	4.3	5.9	15.4	2.9	2.9	3.1	3.2	2.9
$\lambda_{2,p50}$	<b>3.6</b>	<b>5.3</b>	<b>3.9</b>	<b>3.6</b>	<b>3.8</b>	<b>3.3</b>	<b>6.3</b>	<b>5.4</b>	<b>7.2</b>	<b>4.3</b>	<b>3.8</b>	<b>6.0</b>	<b>6.8</b>	<b>3.2</b>
$\lambda_{2,p10}$	2.4	2.9	2.7	2.2	2.6	2.4	3.5	3.0	4.0	2.8	2.5	3.0	3.5	2.2
$\lambda_{2,p90}$	6.8	11.3	6.0	10.1	6.8	5.6	13.3	11.4	14.6	7.9	6.9	13.8	14.0	6.9
$\lambda_{3,p50}$	<b>6.7</b>	<b>3.0</b>	<b>2.6</b>	<b>2.0</b>	<b>6.8</b>	<b>8.4</b>	<b>3.1</b>	<b>2.1</b>	<b>2.2</b>	<b>2.6</b>	<b>3.1</b>	<b>6.1</b>	<b>7.5</b>	<b>6.4</b>
$\lambda_{3,p10}$	3.9	2.2	2.1	2.0	3.5	4.7	2.3	2.0	2.0	2.1	2.3	3.4	3.7	3.1
$\lambda_{3,p90}$	13.7	5.3	3.5	2.1	13.6	16.2	5.1	2.4	2.5	3.8	5.1	12.5	15.6	14.1
$\lambda_{4,p50}$	<b>4.3</b>	<b>8.8</b>	<b>9.1</b>	<b>3.9</b>	<b>8.3</b>	<b>2.5</b>	<b>6.0</b>	<b>10.9</b>	<b>7.9</b>	<b>9.0</b>	<b>5.5</b>	<b>8.3</b>	<b>7.7</b>	<b>6.3</b>
$\lambda_{4,p10}$	2.5	4.7	5.0	2.6	4.5	2.1	3.4	5.9	4.2	4.5	3.5	4.1	4.3	2.9
$\lambda_{4,p90}$	9.0	17.3	18.0	7.1	16.0	3.3	12.8	20.3	16.0	17.8	9.5	15.9	16.4	14.7
$\lambda_{5,p50}$	<b>3.1</b>	<b>2.2</b>	<b>2.2</b>	<b>5.2</b>	<b>2.5</b>	<b>2.3</b>	<b>2.3</b>	<b>2.4</b>	<b>2.5</b>	<b>2.2</b>	<b>2.2</b>	<b>2.5</b>	<b>5.1</b>	<b>2.4</b>
$\lambda_{5,p10}$	2.2	2.0	2.0	3.2	2.1	2.1	2.0	2.1	2.1	2.0	2.0	2.1	2.9	2.1
$\lambda_{5,p90}$	7.1	2.7	2.7	10.2	3.5	3.0	2.8	3.3	3.4	2.5	2.5	3.7	9.9	3.2
$\lambda_{6,p50}$	<b>2.1</b>	<b>2.8</b>	<b>2.3</b>	<b>5.7</b>	<b>2.1</b>	<b>2.0</b>	<b>2.1</b>	<b>3.8</b>	<b>5.7</b>	<b>2.2</b>	<b>2.2</b>	<b>2.2</b>	<b>2.1</b>	<b>2.0</b>
$\lambda_{6,p10}$	2.0	2.1	2.0	3.2	2.0	2.0	2.0	2.5	3.5	2.0	2.0	2.0	2.0	2.0
$\lambda_{6,p90}$	2.4	4.3	2.8	11.4	2.2	2.1	2.4	8.2	10.8	2.7	2.7	2.6	2.3	2.1
$\lambda_{7,p50}$	<b>4.8</b>	<b>3.7</b>	<b>5.3</b>	-	<b>2.8</b>	<b>2.1</b>	<b>9.0</b>	-	-	<b>6.1</b>	<b>5.7</b>	<b>2.9</b>	<b>2.4</b>	<b>4.0</b>
$\lambda_{7,p10}$	2.8	2.4	3.2	-	2.2	2.0	4.5	-	-	3.4	3.2	2.2	2.1	2.5
$\lambda_{7,p90}$	9.6	7.4	10.0	-	4.3	2.4	18.0	-	-	12.0	11.9	4.3	3.2	8.1
$\lambda_{8,p50}$	<b>2.1</b>	-	-	-	-	-	-	-	-	-	-	-	-	-
$\lambda_{8,p10}$	2.0	-	-	-	-	-	-	-	-	-	-	-	-	-
$\lambda_{8,p90}$	2.4	-	-	-	-	-	-	-	-	-	-	-	-	-



**Table 13. Substitution due to bank capital shocks (robustness check).** Table shows the number of shocks that satisfy a set of sign-relations (indicated by +/- at the top part of the table) related to bank capital shock with probability  $p$  higher than 0.25, 0.50, 0.70 or 0.90. The sign relations must hold either on impact or at 12 month lag as indicated in the subheaders.

**a) Substitution between corporate and household borrowers**

	Capital tightening (1–6)						Profitability shock (7–12)					
Sign relations:												
<i>Capital ratio</i>	+	+	+	+	+	+	+	+	+	+	+	+
<i>Relative firm lending spread</i>	+		+	+		+	–		–	–		–
<i>Relative firm lending growth</i>		–	–		–	–		+	+		+	+
<i>Production</i>				–	–	–				+	+	+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<b>Instantaneous response for all variables</b>												
<i>3. Capital ratio, Relative firm lending spread, Relative firm lending growth, Production</i>												
$p \geq 0.25$	72	79	25	26	26	15	74	66	36	26	28	12
$p \geq 0.50$	45	45	5	7	8	3	39	39	9	5	7	1
$p \geq 0.70$	12	21	3	0	3	0	15	8	0	2	3	0
$p \geq 0.90$	3	6	2	0	0	0	2	2	0	0	1	0
<i>4. Capital ratio, Relative firm lending spread, Relative firm lending growth, Production, SovCISS, Corporate loan losses</i>												
$p \geq 0.25$	95	101	35	36	34	20	94	89	40	36	41	11
$p \geq 0.50$	59	56	10	8	13	5	50	53	9	6	12	1
$p \geq 0.70$	18	26	3	1	5	1	19	13	2	2	4	0
$p \geq 0.90$	4	8	2	0	1	0	4	3	0	0	2	0
<b>Instantaneous response for Capital ratio, 12 month response for other variables</b>												
<i>5. Capital ratio, Lending relative to bond markets, Production</i>												
$p \geq 0.25$	79	75	23	41	46	6	66	72	24	25	38	9
$p \geq 0.50$	48	47	5	16	19	3	36	37	8	12	9	1
$p \geq 0.70$	25	17	0	5	7	0	14	14	2	3	3	1
$p \geq 0.90$	6	3	0	1	2	0	2	6	1	1	1	1
<i>6. Capital ratio, Lending relative to bond markets, Production, SovCISS, Corporate loan losses</i>												
$p \geq 0.25$	96	98	39	64	63	8	89	94	35	34	47	12
$p \geq 0.50$	62	50	11	27	24	3	47	59	8	10	8	0
$p \geq 0.70$	26	19	1	8	7	0	15	15	2	5	0	0
$p \geq 0.90$	9	6	0	0	0	0	3	6	1	0	0	0

Number of countries is 14.



## b) Substitution between corporate bank loans and security issuance

	Capital tightening (1–2)		Profitability shock (3–4)	
Sign relations:				
<i>Capital ratio</i>	+	+	+	+
<i>Lending relative to bond markets</i>	–	–	+	+
<i>Production</i>		–		+
	(1)	(2)	(3)	(4)
<b>Instantaneous response for all variables</b>				
5. <i>Capital ratio, Lending relative to bond markets, Production</i>				
$p \geq 0.25$	45	15	39	19
$p \geq 0.50$	34	9	16	7
$p \geq 0.70$	13	1	8	3
$p \geq 0.90$	1	0	3	0
6. <i>Capital ratio, Lending relative to bond markets, Production, SovCISS, Corporate loan losses</i>				
$p \geq 0.25$	62	21	58	28
$p \geq 0.50$	40	6	30	7
$p \geq 0.70$	15	2	9	2
$p \geq 0.90$	3	0	3	0
<b>Instantaneous response for Capital ratio, 12 month response for other variables</b>				
5. <i>Capital ratio, Lending relative to bond markets, Production</i>				
$p \geq 0.25$	43	28	42	22
$p \geq 0.50$	22	8	28	9
$p \geq 0.70$	8	3	9	2
$p \geq 0.90$	1	0	3	0
6. <i>Capital ratio, Lending relative to bond markets, Production, SovCISS, Corporate loan losses</i>				
$p \geq 0.25$	57	32	64	40
$p \geq 0.50$	22	6	48	13
$p \geq 0.70$	7	2	22	5
$p \geq 0.90$	1	0	5	1

Number of countries is 10. For Great Britain, Sweden, Denmark, and Ireland, the bond data was either not available or insufficient in length.

## APPENDIX

**Table A Bank capital shocks by country (instantaneous)** Table shows for each country the number of shocks that satisfy a set of instantaneous sign-relations (indicated by +/- at the top part of the table) related to bank capital shock with probability  $p$  higher than 0.25, 0.50, 0.70 or 0.90.

a) Model 1a, capital tightening shocks

[illegible]

## b) Model 1a, bank profitability shocks

[illegible]

c) Model 1b, capital tightening shocks

[illegible]

## d) Model 1b, bank profitability shocks

[illegible]

e) Model 1c, capital tightening shocks

[illegible]

f) Model 1c, bank profitability shocks

[illegible]

g) Model 2a, capital tightening shocks

[illegible]



#### h) Model 2a, bank profitability shocks

[illegible]

i) Model 2b, capital tightening shocks

[illegible]

## j) Model 2b, bank profitability shocks

[illegible]

k) Model 2c, capital tightening shocks

[illegible]

1) Model 2c, bank profitability shocks

[illegible]

m) Model 3, capital tightening shocks

[illegible]

n) Model 3, bank profitability shocks

[illegible]

m) Model 4, capital tightening shocks

[illegible]

n) Model 4, bank profitability shocks

[illegible]

m) Model 5, capital tightening shocks

Sign pattern		EA	DE	FR	IT	ES	FI	AT	BE	NL	PT	Total
Capital ratio (+),	$p \geq 0.25$	3	2	2	3	3	3	3	2	2	3	26
Lending relative to	$p \geq 0.50$	2	2	2	1	2	3	0	1	2	3	18
bond markets (–)	$p \geq 0.70$	0	1	1	0	2	2	0	1	1	2	10
	$p \geq 0.90$	0	0	1	0	0	0	0	1	0	1	3
Capital ratio (+),	$p \geq 0.25$	1	1	1	0	0	2	1	0	1	1	8
Lending relative to	$p \geq 0.50$	0	1	1	0	0	1	0	0	1	1	5
bond markets (–),	$p \geq 0.70$	0	0	1	0	0	0	0	0	0	0	1
Production (–)	$p \geq 0.90$	0	0	1	0	0	0	0	0	0	0	1

n) Model 5, bank profitability shocks

[illegible]

m) Model 6, capital tightening shocks

Sign pattern		EA	DE	FR	IT	ES	FI	AT	BE	NL	PT	Total
Capital ratio (+),	$p \geq 0.25$	4	4	4	4	5	5	5	3	3	5	42
Lending relative to	$p \geq 0.50$	3	3	3	3	5	4	2	2	2	4	31
bond markets (–)	$p \geq 0.70$	1	0	1	1	2	2	0	2	1	1	11
	$p \geq 0.90$	0	0	1	0	0	0	0	1	0	1	3
Capital ratio (+),	$p \geq 0.25$	0	2	2	1	0	3	3	1	1	2	15
Lending relative to	$p \geq 0.50$	0	0	1	1	0	3	0	0	1	0	6
bond markets (–),	$p \geq 0.70$	0	0	1	1	0	1	0	0	1	0	4
Production (–)	$p \geq 0.90$	0	0	1	0	0	0	0	0	0	0	1

n) Model 6, bank profitability shocks

[illegible]



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