

Sectoral Risk-Weights and Macroprudential Policy

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Abstract

This paper analyses bank capital requirements in a general equilibrium model by evaluating the implications of different designs of such requirements regarding their impact on the tendency of banks to amplify the business cycle. We compare the Basel-established Internal Ratings-Based (IRB) approach to risk-weighting assets with an alternative macroprudential approach which sets risk-weights in response to sectoral measures of leverage. The different methods are compared in a crisis scenario, where the crisis originates from the housing market that affects the banking sector and is then transmitted to the wider economy. We investigate both boom and bust phases of the crisis by simulating an unrealized news shock that leads to a gradual build up and rapid crash in the economy. Our results suggest that the IRB approach creates procyclicality in regulatory capital requirements and thereby works to amplify both boom and bust phases of the financial cycle. On the other hand, our proposed macroprudential approach to setting risk-weights leads to counter-cyclicality in regulatory capital requirements and thereby attenuates the financial cycle.

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1. Introduction

The recent Great Recession is the latest in a long series of financial crises that have demonstrated how the banking sector can promulgate shocks into the real economy. Banking regulation needs to be designed with this reality in mind, and should where possible work to mitigate the inherently procyclical behaviour of banks. In this regard, it is relevant to note that the asset bubbles that cause financial crises tend to be sectoral in nature. Investors have periodic manias, whereby expectations for future growth in particular sectors lead to excessive and unstable credit flows into concentrated areas of the economy.

This paper assesses three different designs for calculating bank capital requirements to understand how they impact on the banking system's tendency to amplify the business cycle. We test and compare the Basel-established Internal Ratings-Based (IRB) approach, the leverage ratio (LR) approach (static risk-weights equal to one for all asset classes), and a macroprudential approach. The macroprudential application of sectoral capital requirements is based on a Taylor-type rule, which alters capital requirements with the credit cycle in each asset class. Capital requirements for a certain asset class increase as credit volumes into that asset class increase, and decrease as credit volumes recede from that asset class. The three policy settings and their effectiveness in stabilizing the economy are compared under two different crisis scenarios which represent closely the 2008 financial crisis. The first scenario represents the crash phase of the crisis, and the second consists of a simulated boom and bust cycle. Our historical variance decomposition identifies an idiosyncratic shock to mortgages as the main driving factor of the crisis. Therefore, we simulate the crisis as originating from a shock to the idiosyncratic risk in the mortgage market.

The analysis takes place in a DSGE model with a detailed banking sector and financial frictions of the type used in [Bernanke et al. \(1999\)](#), hereafter referred to as BGG. The main departure from the BGG set-up is that interest rates are predetermined as in [Quint and Rabanal \(2014\)](#). However, unlike [Quint and Rabanal \(2014\)](#), our analysis models both the banking sector and bank capital dynamics. The basic structure of the banking sector in our paper is closely related to the approaches used in [Gerali et al. \(2010\)](#) and [Angelini et al. \(2014\)](#). Our paper is novel as it introduces bank asset risk-weights in capital requirements to examine their impact on the business cycle.¹

Our results complement the existing related literature. [Angelini et al. \(2010\)](#) provides an overview of many relevant recent papers and provides a useful contribution to the theoretical discussion on how best to design capital regulation. [Gordy and Howells \(2006\)](#) also find potential procyclical features within Basel II, but are more sceptical on the rationale for an anticyclical regulatory response to this. [Repullo and Suarez \(2013\)](#) agree that more advanced Basel methods have increased procyclicality, but nonetheless find advanced Basel methods to be welfare improving given their impact in reducing the incidence of costly bank failure. Using a macro model with optimizing banks that are subject to the possibility of bank runs, [Angeloni and Faia \(2013\)](#) find that risk-based capital requirements amplify the cycle and are welfare detrimental. [Kashyap and Stein \(2004\)](#) provide further support to the increasingly procyclical effects of Basel rules from the first to the second Accord. Numerous empirical studies have also found signs of procyclicality arising from model-based (IRB) regulation. For example, [Behn et al. \(2014\)](#) analyse the impact of model-based capital regulation on the credit risk of financial institutions. Similarly, [Goodhart et al. \(2004\)](#) study among other things the particular impacts of Basel II reforms on the procyclicality of the regulatory system.

Our paper highlights three main results. First, in both boom and bust phases of the crisis the IRB approach leads to the most procyclical capital requirements. In the boom phase, capital requirements become looser - thereby reinforcing the boom

¹[Gerali et al. \(2010\)](#) introduce capital requirements but regard the assets as equally weighted with a weight of one: thereby corresponding to a leverage ratio. [Angelini et al. \(2014\)](#) study the interaction between capital requirements and monetary policy. In contrast to our set-up, where risk-weights on assets are determined endogenously, [Angelini et al. \(2014\)](#) introduce asset risk-weights for the capital requirements according to an ad-hoc rule which relates risk-weights to current and past output procyclically.

by making loans cheaper and more available. In recessions, higher Probabilities of Default (PDs) lead to higher risk-weights and tighter capital regulation thereby depressing bank lending and economic activity. The IRB approach thereby exacerbates a recession by making loans more expensive just at the point where firms need to raise finance. The IRB approach leads to a more substantial decline in investment and output following the shock, and a slower recovery compared to the LR case.

Second, the leverage ratio policy is less procyclical than the IRB approach, but does nothing to counteract the cycle, meaning that the mortgage shock is still strongly transmitted through the banking system into the real economy. During a downturn, the larger default rates destroy bank capital, reducing the capital-asset ratio below the regulatory requirement. In response, banks must increase interest rates on loans to adjust their balance sheets, leading to a prolonged recession.

Third, our macroprudential approach to setting risk-weights is best suited to mitigate the banking sector's tendency to amplify recessions. We find that our macroprudential approach to risk-weighting leads to countercyclicality of capital regulation in both boom and bust phases of the crisis - thereby attenuating business cycles. The negative impact of a severe financial shock on the real economy turns out to be smaller, and the recovery happens faster in comparison to an IRB scenario.

Our results highlight the relative effectiveness of the three different policy settings (IRB, LR, macro prudential tool) in providing stable financing, and smoothening the business cycle. Quantitatively, we assess the relevance of each policy setting in terms of social welfare. Using the Leverage Ratio (LR) as a baseline, the IRB approach leads to a 1.4% decrease in welfare, whereas the macroprudential approach leads to a 0.4% improvement in welfare. In terms of equivalent consumption measures of the changes in welfare, the IRB approach corresponds to a reduction in consumption of around 2% versus the leverage ratio baseline, while the basic macroprudential setting corresponds to a 0.6% increase in consumption.

The macroprudential approach requires certain parameters choices that determine the responsiveness of risk-weights to changes in sectoral leverage. In the baseline case, we have chosen parameters with a relatively modest responsiveness rate so as to avoid overstating the potential effectiveness of the tool. For robustness purposes, we replicate the study using alternative parameters, including ones that maximize social welfare and hence correspond to an "optimal macroprudential rule". Unsurprisingly, the benefits of the macroprudential rule over the IRB (as well as the LR) approach are amplified in this optimal macroprudential case.² The main results of this paper hold for a variety of different types of alternative shocks, including loan supply shocks, monetary policy shocks, technology shocks, and shocks to entrepreneurs' idiosyncratic risk.

Our paper illustrates that the IRB approach has some characteristics that can potentially interfere with the stable flow of credit to the economy. The IRB approach is based upon banks' own estimates of PDs and losses given default (LGDs) of their assets. The estimates of PDs and LGDs are based on historical observations of real data either from the banks' portfolio or potentially drawing from representative external data if justified. At the outset of a recession, it can be expected that the preceding period's PD and LGD observations will be increasing. This backward-looking approach to risk-estimation can therefore result in capital requirements increasing just as a recession is starting.³ Such an effect is not optimal from the perspective of stabilizing capital flows as it could lead a bank towards further deleveraging at the start of a recession. Likewise, on the other side of the business cycle, there may be a tendency for capital requirements to decrease just as a boom phase begins. PDs and LGDs are expected to fall as the economy improves, and this will filter through into reduced capital requirements for banks.

Our findings are potentially relevant for policy-makers. We highlight that model-based capital regulation may tend to exacerbate the procyclical behaviour of banks. To counteract this, policy-makers must be proactive in applying a macroprudential

²If we calibrate the parameters within the macroprudential approach to optimise social welfare, the welfare improvement versus the leverage ratio case increases from 0.4% (under our baseline macroprudential setting) to 0.9%. In terms of equivalent consumption measures of the changes in welfare the optimal macroprudential setting corresponds to an increase in consumption of 1.23%, versus an increase of 0.6% under the baseline macroprudential setting.

³Generally, short horizons are used to compute the PD and LGD, i.e. around five years.

overlay to capital requirements. This is important in order to discourage banks from lending excessively in boom phases and to encourage banks to continue lending when economically difficult periods arise. The macroprudential approach to setting sectoral risk-weights that we have designed and tested in this paper would be one way to provide such an anti-cyclical overlay. In comparison to the Countercyclical Capital Buffer (CCB) approach that is set out in Basel III, our macroprudential approach to setting risk-weights adjusts lending incentives to the sectoral financial cycle. Using risk-weights in this way could add precision to the regulatory framework focusing anti-cyclical impacts on sectors that are experiencing boom times, whilst avoiding unwarranted impacts on non-bubble sectors. This could help to focus the impact of the tool on the right areas of the economy to stabilize capital flows and reduce unintended spillover costs to other sectors.

The rest of the paper is structured as follows. Section 2 outlines the model design, Section 3 explains our approach to calibrating and estimating the model parameters, and Section 4 sets out our results and provides accompanying policy analysis. Finally, Section 5 concludes. A description of the data used for the calibration and estimation of the model parameters can be found in Appendix A. Appendix B provides a detailed derivation of the model equations. Appendix C offers robustness checks and additional results.

2. Model

This paper provides a dynamic stochastic general equilibrium model with a banking sector, closely related to [Gerali et al. \(2010\)](#) and [Angelini et al. \(2014\)](#). The model is used as a laboratory for the comparison of the IRB approach versus a macroprudential asset-risk-weight setting rule in stabilizing the economy during recessions. The model is populated by entrepreneurs, heterogeneous households, and monopolistically competitive banks and firms. This section describes the agents in the model as well as the direct impact of the macroprudential policy rule.

2.1. Heterogeneous Households

Savers

Each saver (or patient household) i maximizes expected lifetime utility subject to the budget constraint

$$\begin{aligned} \max E_0 \sum_{t=0}^{\infty} (\beta^P)^t & \left[(1 - \alpha^P) \varepsilon_t^c \log(C_t^P(i) - \alpha^P C_{t-1}^P) + \varepsilon_t^h \log(H_t^P(i)) - \frac{(L_t^P(i))^{1+\phi}}{1+\phi} \right] \\ \text{s.t. } C_t^P + q_t^h \Delta H_t^P + D_t &= W_t^P L_t^P + \frac{R_{t-1} D_{t-1}}{\pi_t} + T_t \end{aligned}$$

Expected lifetime utility depends on current individual (and lagged aggregate) consumption C_t^P , housing H_t^P and hours worked L_t^P .⁴ The last term is labour disutility where ϕ denotes the inverse elasticity of labour supply. There are two preference shocks present, ε_t^c affects the marginal utility of consumption, and ε_t^h the marginal utility of housing.

The patient household spends his income on current consumption, accumulation of housing (with q_t^h denoting real house prices), and on saving via real deposits D_t . The income side consists of wage earnings $W_t L_t^P$ (where W_t is the real wage), and gross interest income from last period deposits $R_{t-1} D_{t-1} / \pi_t$, where $\pi_t = P_t / P_{t-1}$ is gross inflation and R_{t-1} denotes the gross interest rate on deposits. T_t includes profits from intermediate goods producers and from debt repossession agencies.

⁴Pre-multiplying by the habit coefficient α^P offsets the impact of external habits on the steady-state marginal utility of consumption.

Borrowers

Borrowers (or impatient households) differ from savers in several aspects. First, their discount factor is smaller than the one of the savers ($\beta^I < \beta^P$) which means that they are more impatient to consume. Due to their impatience, in equilibrium, savers are willing to accumulate assets as deposits, and borrowers are willing to offer their housing wealth as collateral to obtain loans. Second, the borrowers don't earn profits from goods producers. And third, borrowers are subject to a quality shock ω^j to the value of their housing stock which leads to loan default for some of them.

Analogously to savers, each borrower i , maximizes expected lifetime utility subject to the budget constraint and default threshold $\bar{\omega}_t^{p,I5}$:

$$\begin{aligned} \max E_0 \sum_{t=0}^{\infty} (\beta^I)^t & \left[(1 - \alpha^I) \varepsilon_t^c \log(C_t^I(i) - \alpha^I C_{t-1}^I) + \varepsilon_t^h \log(H_t^I(i)) - \frac{(L_t^I(i))^{1+\phi}}{1+\phi} \right] \\ \text{s.t. } C_t^I + q_t^h \Delta H_t^I + q_t^h H_{t-1}^I G_t^{I,p} + \frac{(1 - F_t^{I,p}) r_{t-1}^I B_{t-1}^I}{\pi_t} &= B_t^I + W_t^I L_t^I \\ \bar{\omega}_t^{p,I} &= \frac{r_{t-1}^I B_{t-1}^I}{q_t^h H_{t-1}^I \pi_t} \end{aligned} \quad (2.1)$$

The budget constraint for borrowers differs among those who default and those who repay their loans. Aggregating borrowers' budget constraints⁶ and dropping the i superscripts, yields (2.1).⁷ A detailed description of the logic of default and its equations is provided in the section describing Banks 2.3.

2.2. Firm sector

Entrepreneurs

Entrepreneurs maximize the sum of expected lifetime utility subject to the budget constraint, production function and the default threshold $\bar{\omega}_t^{p,E}$:

$$\begin{aligned} \max_{\{C_t^E, K_t^E, B_t^E, L_t^P, L_t^I\}} E_0 \sum_{t=0}^{\infty} (\beta^I)^t & \left[(1 - \alpha^E) \log(C_t^E(i) - \alpha^E C_{t-1}^E) \right] \\ \text{s.t. } C_t^E + W_t^P L_t^P + W_t^I L_t^I + \frac{(1 - F_t^{E,p}) r_{t-1}^E B_{t-1}^E}{\pi_t} + q_t^k [K_t^E - (1 - \delta) K_{t-1}^E] & \\ + q_t^k K_{t-1}^E G_t^{E,p} &= \frac{Y_t^E}{X_t} + B_t^E \end{aligned} \quad (2.2)$$

$$Y_t^E = A_t^E K_{t-1}^{E-1} L_t^{E1-\alpha} \quad (2.3)$$

$$\bar{\omega}_t^{p,E} = \frac{r_{t-1}^E B_{t-1}^E}{q_t^K K_{t-1}^E \pi_t}$$

The entrepreneur i 's utility depends on the deviations of his consumption $C_t^E(i)$ from the aggregated lagged level.⁸ The entrepreneur chooses consumption C_t^E , physical capital K_t^E , loans from banks B_t^E , and labour (L_t^P, L_t^I) . Entrepreneurs have the

⁵All variables and parameters with the superscript I indicate that they are specific to borrowers.

⁶We make the assumption that the households are members of a dynasty and insure themselves after the realization of the shock, thus becoming ex-post identical ensuring representative agent solution.

⁷The last two terms on the LHS of (2.1) denote the average repossessed value of collateral of those who default and repayment of credit by those who don't default. Since those terms arise from the aggregated budget constraint and not from the individual one, we assume that the individual agent does not take into account the probability of not repaying the loan tomorrow when borrowing today. Similarly, we assume that the agents do not consider the probability to defaulting tomorrow when choosing collateral stock today. A similar assumption is made for entrepreneurs. The latter terms are calculated using the ex-post realized threshold separating defaulting from non-defaulting households $\bar{\omega}_t^{p,I}$. Refer to appendix 7.3.

⁸Group habits are parameterized by α^E .

same discount factor as borrower households, such that entrepreneurs become net borrowers in equilibrium, willing to pledge capital used for production as collateral.

The depreciation rate of capital is denoted by δ , q_t^k denotes the price of capital and $P_t^W/P_t = 1/X_t$ is the relative competitive price of the wholesale good Y_t^E that is produced according to the Cobb-Douglas production technology (2.3), where A_t^E denotes a stochastic productivity shock. Aggregate labour, denoted by L_t^E , is given by $L_t^E = (L_t^P)^\nu (L_t^I)^{1-\nu}$, where ν measures the labour income share of patient households.

Capital Producers

Capital producers are a modeling device to derive the price of capital. Capital producers are perfectly competitive. To produce capital, capital producers buy two inputs. First, last-period undepreciated capital $(1 - \delta)K_{t-1}$ at price Q_t^k (the nominal price of capital) from entrepreneurs. Second, I_t units of the final consumption good from retailers at price P_t . The accumulation of capital is given by $\Delta \bar{x}_t = K_t - (1 - \delta)K_{t-1}$. The new stock of effective capital \bar{x}_t is sold back to entrepreneurs at price Q_t^k . In addition, the transformation of the final good into new capital is subject to adjustment costs κ_i . Capital producers maximization problem is given by

$$\begin{aligned} \max_{\{\bar{x}_t, I_t\}} \quad & E_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^E (q_t^k \Delta \bar{x}_t - I_t) \\ \text{s.t.} \quad & \bar{x}_t = \bar{x}_{t-1} + \left[1 - \frac{\kappa_i}{2} \left(\frac{I_t \varepsilon_t^{qk}}{I_{t-1}} - 1 \right)^2 \right] I_t \end{aligned} \quad (2.4)$$

where ε_t^{qk} denotes a shock to investment efficiency, and $q_t^k \equiv \frac{Q_t^k}{P_t}$ the real price of capital.

Retailers

We follow [Bernanke et al. \(1999\)](#) regarding the structure of the retail good market. We assume monopolistic competition. Retail prices are sticky and are indexed to a combination of past and steady-state inflation, with relative weights parameterized by ι_p . Whenever retailers want to change prices beyond this indexation allowance, they face a quadratic adjustment cost parameterized by κ_p . Retailer i chooses $P_t(i)$ subject to the consumers demand function (2.5)

$$\begin{aligned} \max_{P_t(i)} \quad & E_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^P \left[P_t(i) Y_t(i) - P_t^W Y_t(i) - \frac{\kappa_p}{2} \left(\frac{P_t(i)}{P_{t-1}(i)} - \pi_{t-1}^{\iota_p} \pi^{1-\iota_p} \right)^2 P_t Y_t \right] \\ \text{s.t.} \quad & Y_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\varepsilon_t^y} Y_t \end{aligned} \quad (2.5)$$

where π denotes steady state inflation, and ε_t^y the stochastic demand price elasticity.

2.3. Banks

The banking sector consists of a wholesale branch and two retail branches. The wholesale branch manages the capital-asset position of the bank as it accumulates bank capital out of retained earnings and pays a quadratic cost whenever it deviates from a risk-weighted capital-asset requirement. As bank capital can only be accumulated through retained earnings, the supply of credit is constrained as imposed by the Basel regulation. The two retail branches obtain funds from the wholesale branch and lend them to households and firms respectively. The two types of loans are non-recourse with pre-determined interest rates - this allows for unexpected changes in the collateral prices to be transmitted to the loan default rates. These unexpected changes

lead to profits/losses that affect the capital-asset position of the banking sector.

2.3.1. Wholesale branch

The wholesale branch collects deposits D at the gross policy rate R which together with the accumulated bank capital K^b is used to fund its loans B , leading to a balance sheet identity

$$B_t = D_t + K_t^b \quad (2.6)$$

where the two sources of funding, K^b and B , are perfect substitutes. Bank capital is accumulated through retained earnings

$$K_t^b = (1 - \delta^b)K_{t-1}^b + \Pi_t$$

where δ^b is the depreciation rate of bank capital, and should be interpreted as the costs of managing bank capital. Π_t denotes the realized overall profits of all bank branches, including the profits of the wholesale Π_t^{ws} and the two retail branches profits Π_t^h and Π_t^f

$$\Pi_t = \Pi_t^{ws} + \Pi_t^h + \Pi_t^f$$

The overall loans B_t in the economy consist of the loans B_t^I and B_t^E that the two retail branches lend to households and firms, respectively. The retail branches obtain the funds to lend from the wholesale branch at the gross interest rates $R^{b,I}$ and $R^{b,E}$ respectively.

The wholesale branch maximizes profits taking into account a quadratic cost QC_t whenever the risk-weighted capital-asset ratio K_t^b/RWA_t deviates from an exogenous level ν^b which represents the regulatory capital requirement.⁹

$$QC_t = \frac{\kappa_b}{2} \left(\frac{K_t^b}{RWA_t} - \nu^b \right)^2 K_t^b$$

where RWA_t denotes the risk-weighted assets and is given by the weighted sum of each asset type. The asset specific weights w_t^I and w_t^E represent a regulatory instrument that allows for adjusting the risk-weight of a specific asset class.

$$RWA_t = w_t^I B_t^I + w_t^E B_t^E \quad (2.7)$$

Thus the wholesale branch maximization problem is given by

$$\begin{aligned} \max_{\{D_t, B_t^I, B_t^E\}} \quad & E_0 \sum_{i=0}^{\infty} \Lambda_{0,t} \left[(R_t^{b,I} - 1)B_t^I + (R_t^{b,E} - 1)B_t^E - (R_t - 1)D_t - QC_t \right] \\ \text{s.t.} \quad & B_t = D_t + K_t^b \end{aligned}$$

The wholesale branch maximizes its profits subject to the balance sheet identity (2.6) by taking $R_t^{b,I}$, $R_t^{b,E}$ and R_t as given.

Using the FOCs, we can write

$$R_t^{b,j} - R_t = \kappa_b \left(\nu^b - \frac{K_t^b}{RWA_t} \right) \left(\frac{K_t^b}{RWA_t} \right)^2 w_t^j \quad \text{for } j \in \{I, E\} \quad (2.8)$$

⁹The quadratic cost for deviating from the regulatory requirement can be thought of as a simple shortcut for studying the implications and costs of regulatory capital requirements as in [Gerali et al. \(2010\)](#). In reality, similar trade-offs would arise from banks' decision of how much own resources to hold.

Equation (2.8) links the interest rate spread $R_t^{b,j} - R_t$ for each loan type $j \in \{I, E\}$ to the degree of deviation of the capital-asset ratio from its requirement ν^b , as well as to the loan specific risk-weight w_t^j . The LHS of equation (2.8) represents the marginal benefit from increasing lending of type j (an increase in profits equal to the interest rate spread), while the RHS represents the marginal cost of doing so (an increase in the costs for deviating from ν^b). Therefore, the wholesale branch chooses a level of each type of lending j which, at the margin, equalizes costs and benefits of changing the capital risk-weighted asset ratio.

2.3.2. The retail branches

The retail branches face endogenous loan defaults due to an idiosyncratic shock to the collateral value of borrowers and the non-recourse contract with predetermined interest rates. Unlike the wholesale branch, each retail branch has the necessary and specialized expertise for its type of lending - to evaluate expected collateral prices and default rates. One retail branch is specialized in mortgage loans - the branch denoted by $j = I$ provides loans to households against housing collateral. The second retail branch $j = E$ lends to firms (entrepreneurs) against capital collateral. Apart from their different specialization, both retail branches are identical. For future reference, ex-ante expected and ex-post realized variables are denoted with a and p superscripts respectively. There are neither agency problems nor asymmetric information, hence bank retail branches are perfectly competitive and make zero profits in expected terms. The retail branch j obtains funds from the wholesale branch and takes the interest rate $R^{b,j}$ that the wholesale branch charges as given. According to the riskiness of the loans, i.e. their probability of default, the retail branch sets the interest rate on its loans r^j .

The default condition for borrower j is given by

$$\frac{r_{t-1}^j B_{t-1}^j}{\pi_t} \leq \omega_{t-1}^j q_t^j h_{t-1}^j \quad (2.9)$$

If the inequality (2.9) is satisfied the borrower does not default, i.e. when the amount to repay is smaller than the value of the collateral after the realization of the idiosyncratic shock ω_t . The idiosyncratic shock is log-normally distributed with CDF $F(\omega)$, PDF $f(\omega)$ and mean $E(\omega_t) = 1$.¹⁰ At period t , high enough realizations of ω_{t-1} will induce the borrower to repay his loan in full: $r_{t-1}^j B_{t-1}^j / \pi_t$, where r^j is the gross borrowing rate and B^j the quantity borrowed from retail branch j . Low enough realizations will cause the borrower to default and give up his collateral after the realization of the shock: $\omega_{t-1}^j q_t^j h_{t-1}^j$, where q^j denotes the collateral price and h^j denotes the amount of collateral.

In period t , the cut-off value of $\bar{\omega}_{t-1}^j$, i.e. the ex-post realized threshold value $\bar{\omega}_t^p$, that separates borrowers that default and those that do not can be expressed as

$$\bar{\omega}_{t-1}^j \equiv \bar{\omega}_t^{j,p} = \frac{r_{t-1}^j B_{t-1}^j}{q_t^j h_{t-1}^j \pi_t}$$

At period t , the retail branch extends loans at a rate r_t^j without knowing the exact value of the default threshold, since it will also depend on the period $t+1$ collateral price q_{t+1}^j and next period inflation. The retail branch forms ex-ante expectations on $\bar{\omega}_t^{j,a}$

$$\bar{\omega}_t^{j,a} = \frac{r_t^j B_t^j}{E(\pi_{t+1} q_{t+1}^j) h_t^j} \quad (2.10)$$

Note that $\bar{\omega}_t^{j,a}$ equals the retail branch's expected LTV ratio of loan type j .

¹⁰This implies that the log of ω is normally distributed: $\log(\omega_t) \sim N(-\frac{\sigma_\omega^2}{2}, \sigma_\omega^2)$. There is idiosyncratic but no aggregate risk.

Unlike the wholesale branch, retail branches¹¹ do not maximize profits but simply require that the expected return from a unit of credit equals the cost of funds (the rate at which the funds are obtained from the wholesale branch rate $R^{b,j}$). This leads to the following participation constraint

$$R_t^{b,j} = (1 - \mu)G_t^{j,a} \frac{E_t(\pi_{t+1}q_{t+1}^j)h_t^j}{B_t^j} + (1 - F_t^{j,a})r_t^j \quad (2.11)$$

where the RHS of (2.11) consists of the expected return in the case of default (i.e. the repossessed collateral) and the expected return in the case of non-default (i.e. the repayment of the loan). $G_t^{j,a} \equiv G(\bar{\omega}_t^{j,a}, \sigma_{\omega,t}^j) = \int_0^{\bar{\omega}_t^{j,a}} \omega dF(\omega, \sigma_{\omega,t}^j)$ denotes the expected value of the idiosyncratic shock, conditional on the shock being less than $\bar{\omega}_t^{j,a}$; and $1 - F_t^{j,a} \equiv 1 - F(\bar{\omega}_t^{j,a}, \sigma_{\omega,t}^j) = \int_{\bar{\omega}_t^{j,a}}^{\infty} f(\omega, \sigma_{\omega,t}^j) d\omega$ being the probability that the shock exceeds the ex-ante threshold $\bar{\omega}_t^{j,a}$, i.e. the probability of non-default. Banks can repossess only a fraction $1 - \mu$ of the collateral as the remainder is assumed to be lost as a cost of default.

Rearranging the participation constraint (2.11) yields

$$\frac{r_t^j}{R_t^{b,j}} = \frac{1}{\frac{(1-\mu)G_t^{j,a}}{\bar{\omega}_t^{j,a}} + (1 - F_t^{j,a})} \quad (2.12)$$

where the retail spread of each type of loan $j \in \{I, E\}$ is expressed as a function of the expected default threshold $\bar{\omega}_t^{j,a}$. Due to the properties of the log-normal distribution with $E_t(\omega) = 1$, it can be shown that the denominator of the RHS of (2.12) is a decreasing function in ex-ante threshold $\bar{\omega}_t^{j,a}$, and hence, the interest rate spread becomes an increasing function of $\bar{\omega}_t^{j,a}$.¹²

$$\frac{r_t^j}{R_t^b} = f(\bar{\omega}_t^{j,a}); \quad f'(\bar{\omega}_t^{j,a}) > 0$$

The intuition behind this relationship is the following: For a larger expected LTV ratio (RHS of equation (2.10)), a larger proportion of loans is expected to default, and hence the ex-ante threshold $\bar{\omega}_t^{j,a}$ increases. Since the threshold separates the defaulting from non-defaulting loans, the bank would expect a larger default area and a smaller non-default area given by $(1 - F_t^{j,a})$. In order to compensate for the larger expected defaults, the retail branches increase the loan rate r_t^j .

2.3.3. Bank profits

The participation constraint (2.11) ensures that the retail branches make zero profits in expected terms. However, due to the predetermined interest rate and as a consequence of shocks, the participation constraint does not always hold ex-post. This can occur due to the aggregate risk that cannot be insured by the retail branches. For example, an unexpected increase of the collateral price would lead to lower ex-post threshold than the one expected last period when the loan was issued: $\bar{\omega}_t^{j,p} < \bar{\omega}_{t-1}^{j,a}$. Hence, a smaller fraction of borrowers would be below the threshold and default. The decrease in the default rate and the price increase of the repossessed collateral would lead to positive profits for the respective retail branch and these profits would be accumulated as bank capital.

Thus ex-post profits of loan type j are given by

$$\Pi_t^j = (1 - \mu)G_t^{j,p}q_t^j h_{t-1}^j \pi_t + (1 - F_t^{j,p})r_{t-1}^j B_{t-1}^j - R_{t-1}^{j,b} B_{t-1}^j$$

¹¹Although the retail branches do not maximize profits, since we consider each bank as composed of one wholesale and two retail branches we can say that each bank operates under monopolistic competition with profit maximization occurring at the wholesale level.

¹²Refer to appendix 7.1.

that is, the sum of the average repossession value of collateral for the defaulted loans and the loan repayment of non-defaulted loans, minus the cost of funds for the bank.

It can be shown that the profit of each branch is a function of the difference between last period's ex-ante expected and current period's ex-post realized thresholds.¹³ Whenever the two thresholds are equal, profits are zero. When the ex-post threshold is smaller than expected (i.e. a smaller proportion of loans default than expected) profits are positive

$$\Pi_t^j = f(\bar{\omega}_{t-1}^{j,a} - \bar{\omega}_t^{j,p}), f'() > 0$$

Figure (1) gives an overview of the different interest rate spreads in the economy and the factors that affect them. The asset-specific interest rate spreads determine the borrowing costs of households and firms and hence the quantities of specific loan types in the economy. The wholesale spreads ($R^b - R$, $R^{b,I} - R^b$, $R^{b,E} - R^b$) are affected by the capital asset position of the banking sector and the composition of the loan portfolio. The two retail spreads ($r^I - R^{b,I}$ and $r^E - R^{b,E}$) are affected by the expected collateral values and expected default threshold of each type of loan.

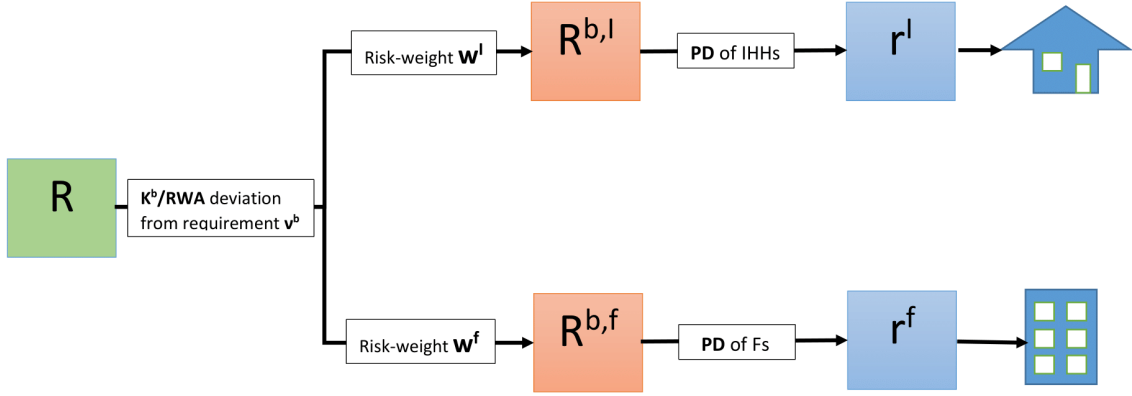


Figure 1: Interest rate spreads structure

The above two-level representation of spreads can also be interpreted from the perspective of the Basel capital regulation. While the retail level spread arises due to provisioning of expected losses by retail branches, the wholesale level spread arises due to capital regulation which aims to address the possibility of unexpected losses which are covered by bank capital.

2.4. Policy

2.4.1. Monetary Policy

The central bank sets the deposit interest rate according to the following Taylor rule

$$R_t = (R)^{(1-\phi_R)} (R_{t-1})^{\phi_R} \left(\frac{\pi_t}{\pi} \right)^{\phi_\pi (1-\phi_R)} \left(\frac{Y_t}{Y_{t-1}} \right)^{\phi_Y (1-\phi_R)} \varepsilon_t^r \quad (2.13)$$

where ϕ_π and ϕ_Y denote the weights of inflation and output, R the steady state policy rate and ε^r the monetary policy shock. Changes in policy rate R_t will affect all interest rates equally, without affecting any of the interest rate spreads shown in Figure (1).

¹³See appendix 7.2

2.4.2. Macroprudential policy

Equation (2.8) allows the analysis of how different macroprudential instruments impact the asset specific interest rate spreads. In turn, the asset specific interest rate spreads determine the borrowing costs of households and firms and hence the volumes of loans to different sectors of the economy. For convenience, equation (2.8) is repeated here

$$R_t^{b,j} - R_t = \kappa_b \left(\nu^b - \frac{K_t^b}{RWA_t} \right) \left(\frac{K_t^b}{RWA_t} \right)^2 w_t^j \quad \text{for } j \in \{I, E\}$$

Keeping everything else constant, an increase of the capital-asset requirement ν^b increases the interest rate spread $R_t^{b,j} - R$ for all loan types j . The impact of this instrument is not asset type specific, it affects the spread of both loan types alike. This is because, ν^b changes the requirement for the capital-asset ratio without changing the risk-weighting of the different types of lending that compose the RWA denominator.

In contrast, an increase of the risk-weight w_t^j of a specific loan type $j \in \{I, E\}$ will have a stronger impact on interest rate spread ($R_t^{b,j} - R^b$) of the loan type j relative to $j' \neq j$. However, the interest rate spread of loan type j' will also be affected through an increase in the risk-weighted assets (RWA) defined by (2.7). This creates the possibility for macroprudential policy to conduct tailored interventions in order to influence bank lending behaviour. For example, by increasing the risk-weight on mortgages and maintaining or decreasing the risk-weight for corporate loans, the macroprudential regulator can alter the relative cost of the two types of lending.

Under our macroprudential approach, the policy maker sets risk-weight w_t^j for asset j according to a Taylor-type rule that responds to credit-to-GDP measures. According to (ESRB, 2014), the credit-to-GDP ratio is an empirically sound basis for designing macroprudential interventions. Fluctuations in this ratio are historically associated with episodes of financial instability whereby the banking sector can destabilise the real economy. In our setup, the macroprudential Taylor-type rule takes the form

$$w_t^j = (\bar{w}^j)^{(1-\rho_w)} (w_{t-1}^j)^{\rho_w} \left(\frac{B_t^j/Y_t}{\bar{B}^j/\bar{Y}} \right)^{\chi_w(1-\rho_w)}$$

The risk-weight of loans to households and firms are set according to the deviation of the loan-specific measure of leverage (B_t^j/Y_t) from its steady state, where the parameters χ_w and ρ_w represent the responsiveness of the instrument to the sectoral leverage measure and its autoregressive properties. In Section 4, we discuss our macroprudential setting of risk-weights in further detail and compare its results to the leverage ratio capital requirements and the current regulatory setting known as the Internal ratings-based approach - IRB.

2.5. Market clearing and shock processes

The equilibrium in the good market can be expressed by the resource constraint, i.e. the aggregated budget constraint of the entrepreneurs, equation (2.2), where C_t denotes aggregate consumption and is given by $C_t = C_t^E + C_t^I + C_t^P$, while $Y^E = A_t^E K_{t-1}^E L_t^E$. The assumption that the housing stock exists in fixed supply, $\bar{H} = 1$, leads to the house market clearing condition

$$\bar{H} = H_t^P + H_t^I \quad (2.14)$$

Shock processes

The shock processes we employ, are specified in Table 3, and have an AR(1) form. The scenario with news shocks is simulated by a negative shock to the expected exogenous term four periods in the future. Then at period 4 a positive shock is simulated

and the two impulse responses are added. This cancels the shock itself and the resulting responses of the variables are entirely due to changes in expectations. In particular, the shock to idiosyncratic risk to mortgages takes the form $\sigma_t^i = \bar{\sigma}^i + \rho^{\sigma^i} (\sigma_{t-1}^i - \bar{\sigma}^i) - \epsilon_{t-4}^{\sigma^i}$ and $\sigma_{t+4}^i = \bar{\sigma}^i + \rho^{\sigma^i} (\sigma_{t+3}^i - \bar{\sigma}^i) + \epsilon_{t+4}^{\sigma^i}$.

3. Parameter Calibration and Estimation

3.1. Methodology and Data

We use standard Bayesian methods and choose prior distributions for the model parameters. First, the dynamics of the model are obtained by taking a log-linear approximation of equilibrium conditions around the steady state. The solution takes the form of a state-space model and allows us to compute the likelihood function. For the estimation of the implied posterior distribution of the parameters, we use the Metropolis-Hastings algorithm, which combines the prior distribution over the model's parameters with the likelihood function.¹⁴

The main data sources are Eurostat and the ECB. The data covers the time period January 2000 to December 2014. The dataset includes twelve variables for the Euro Area with quarterly frequency covering the time period 2000:1 to 2014:4. Data is collected on real consumption, real investment, real house prices, real loans to households and firms, real deposits, real wages, inflation, interest rates to households and firms and the policy (deposit) rate. Following the literature ([Angelini et al. \(2014\)](#), [Gerali et al. \(2010\)](#), [Iacoviello and Neri \(2010\)](#)), variables involving a trend component are made stationary using the HP filter.¹⁵ These variables include consumption, investment, house prices, wages, borrowing of households and firms, and deposits. Consistent with the model solution, the data series are transformed to log deviations from their HP-filtered trend. Interest rates and the inflation rate are demeaned. The time-series of the data is shown in the appendix A, Figure (12). Appendix A also provides a detailed description of the data.

3.2. Calibration of Model Parameters

Table (1) summarizes the calibration of the model parameters. Some model parameters are calibrated to match data or have been taken directly from the literature. The model is calibrated so that each period represents a quarter. The discount factor of patient households β^P is set to 0.9939 which pins down a quarterly steady state policy (deposit) interest rate of 0.60 percent (2.5 percent annualized), which is consistent with the average policy rate in the Euro Area in our data sample. Discount factors for impatient households and entrepreneurs β^I and β^E are calibrated such that we match steady state quarterly borrowing rates of 0.98 and 1.1 percent (4 and 4.5 percent annualized), respectively. The calibrated discount factors are in line with the suggested range in the literature, see for a discussion [Iacoviello \(2005\)](#). These borrowing rates are consistent with the average borrowing rates for mortgages and corporate loans in our data sample.

For the calibration of the LTV steady-state ratios we follow [Gerali et al. \(2010\)](#). We set the LTV of households loans (i.e. mortgages) $\bar{\omega}^I$ to 0.7 and for entrepreneurs $\bar{\omega}^E$ to 0.35. In the steady-state, the two LTVs together with the standard deviations of the idiosyncratic shock $\bar{\sigma}_\omega^j$ pin down the default rates of loan type j . Hence, similarly to [Quint and Rabanal \(2014\)](#) we set the standard deviation of households' idiosyncratic shock $\bar{\sigma}_\omega^I$ such that we match the average default rate of mortgages for the Euro area of 2.5 percent. For firms, we calibrate the standard deviation of entrepreneurs' idiosyncratic shock $\bar{\sigma}_\omega^E$ to 0.47 to

¹⁴See [Smets and Wouters \(2003\)](#). The posterior distributions are based on 200,000 draws of the Metropolis-Hastings algorithm. The estimation is done using Dynare 4.4.3.

¹⁵We follow [Hodrick and Prescott \(1997\)](#) and set the smoothing parameter for quarterly data to 1600.

match a default rate 2.5 percent.¹⁶

The collateral repossession cost parameters of households and firms of (μ^I, μ^E) are implied by the interest rates, LTV ratios and standard deviations of idiosyncratic shocks.

The calibration values for the capital share, the frisch elasticity, depreciation rates, and mark-ups are taken from the literature. We follow Gerali et al. (2010) and set the capital share to 0.25 and the depreciation rate to 0.025. As common in the literature, we assume a mark-up of 20% in the good market and hence set ϵ^Y to 6. For the calibration of the markup in the labor market, we follow Gerali et al. (2010) and set ϵ^l to 5, implying a mark-up of 15%.

The capital-asset requirement ν^b is set to 0.08, consistent with the Basel II regulation. The parameter δ^b , the bank capital depreciation rate, is set to 0.0061.¹⁷

<i>Parameter</i>	<i>Description</i>	<i>Value</i>
β^P	Patient households' discount factor	0.9939
β^I	Impatient households' discount factor	0.9902
β^E	Entrepreneurs' discount factor	0.9890
ϕ	Inverse Frisch elasticity	1
α	Capital share in the production function	0.25
δ	Capital depreciation rate	0.025
ϵ^Y	$\frac{\epsilon^Y}{\epsilon^Y - 1}$ markup in the goods market	6
ϵ^l	$\frac{\epsilon^l}{\epsilon^l - 1}$ markup in the labour market	5
$\bar{\omega}^I$	Households LTV ratio	0.7
$\bar{\omega}^E$	Firms LTV ratio	0.35
$\bar{\sigma}_\omega^I$	Standard deviation of households' idiosyncratic shock	0.17
$\bar{\sigma}_\omega^E$	Standard deviation of households' idiosyncratic shock	0.47
δ^b	Bank capital depreciation rate	0.0061
μ^I	Collateral repossession cost, households	0.093
μ^E	Collateral repossession cost, firms	0.049
ν^b	Capital-asset requirement	0.08

Table 1: Calibrated Parameters

3.3. Estimation (Metropolis-Hastings algorithm)

Table (2) lists the prior and posterior distributions of the remaining model parameters that we estimate using Bayesian methods. The table also shows the 90 percent credible set of selected estimated parameters. Table (3) presents the prior and posterior distributions of the estimated parameters of the shock processes. We are using a Monte-Carlo based optimization technique

¹⁶Due to data availability constraints, we cannot differentiate between default rates of mortgages and corporate loans in the data. The average default rate for all types of loans is 2.5 percent for the Euro area.

¹⁷In our model, banks make profits in the steady state, and the depreciation rate δ^b is set such that it consumes the steady state profits, so that bank capital stays constant at the steady state.

for computing the mode with ten parallel chains for the Metropolis-Hastings algorithm with 200,000 replications each.¹⁸ The scale parameter of the jumping distribution's covariance matrix is set to 0.4 which leads to an average acceptance ratio of 33%.¹⁹

Prior Distributions. We use inverse gamma priors for the standard errors of the shocks. For the persistence, we choose a beta-distribution with a prior mean of 0.8 and standard deviation of 0.1. We set the prior mean of the habit parameters at 0.5, with a standard deviation of 0.1. For the remaining parameters we use prior distributions as in [Gerali et al. \(2010\)](#).

Posterior Distributions. We restrict ourself to commenting on the parameters, where its posterior mean differs significantly from its prior. The posterior mean of the retailer's price indexation is relatively low. However, this finding matches the finding of [Gerali et al. \(2010\)](#) and confirms [Benati \(2008\)](#) who document a reduction in indexation in the euro area in their post-1999 sample.

		Prior Distribution			Posterior Distribution		
	Parameter	Distribution	Mean	St.Dev	Mean	Mode	90% HPD
κ_b	Bank capital adj. cost	Gamma	10	5	0.79	0.78	0.47:1.13
κ_i	Capital adj. cost	Gamma	2.5	1	3.74	2.79	1.84:5.53
κ_p	Retailers' price adj. cost	Gamma	50	20	38.51	39.20	30.26:46.08
ι_p	Retailers' price index	Beta	0.5	0.15	0.18	0.16	0.07:0.29
α_h	Habit coefficient	Beta	0.5	0.1	0.49	0.49	0.33:0.65
ϕ^R	TR AR coefficient	Beta	0.75	0.1	0.70	0.71	0.64:0.77
ϕ^π	TR inflation coefficient	Gamma	2	0.5	1.48	1.38	1.26:1.72
ϕ^Y	TR output coefficient	Normal	0.1	0.15	0.08	0.14	-0.07:0.24

Table 2: Prior and Posterior Distribution of Estimated Structural Parameters

¹⁸In appendix C, section 8.1, we report a robustness check using a single chain of length 500,000. The summary statistics for the posterior distribution did not change.

¹⁹We follow [Brooks and Gelman \(1998\)](#) and compute multivariate convergence statistics for the mean, variance and skewness. We find that the statistics show convergence of the Metropolis algorithm. Second, and following [Geweke \(1992\)](#) we compute convergence diagnostics using a chi-squared test to compare the means of the first and last draw in the simulation. The resulting p-value are significant at the 5% level confirming that the estimated parameters converge. See Appendix C, section 8.1, for more details on the convergence analysis of the metropolis algorithm.

		Prior Distribution			Posterior Distribution		
	Parameter	Distribution	Mean	St.Dev	Mean	Mode	90% HPD
ρ_c	Consumption pref.	Beta	0.8	0.1	0.97	0.98	0.95:0.99
ρ_h	Housing pref.	Beta	0.8	0.1	0.73	0.75	0.68:0.79
ρ_k	Capital adj. cost	Beta	0.8	0.1	0.65	0.64	0.52:0.78
ρ_A	Technology	Beta	0.8	0.1	0.97	0.98	0.95:0.99
ρ_{σ_i}	HHs idiosync.	Beta	0.8	0.1	0.10	0.10	0.10:0.10
ρ_{σ_e}	Es idiosync.	Beta	0.8	0.1	0.93	0.93	0.90:0.95
σ_c	Consumption pref.	Inv. gamma	0.01	0.05	0.007	0.007	0.006:0.008
σ_h	Housing pref.	Inv. gamma	0.01	0.05	0.03	0.02	0.02:0.03
σ_k	Capital adj. cost	Inv. gamma	0.01	0.05	0.01	0.01	0.01:0.02
σ_A	Technology	Inv. gamma	0.01	0.05	0.01	0.01	0.009:0.015
σ_r	Monetary Policy	Inv. gamma	0.01	0.05	0.001	0.0017	0.001:0.002
σ_{σ_i}	HHs idiosync.	Inv. gamma	0.01	0.05	0.55	0.55	0.47:0.64
σ_{σ_e}	Es idiosync.	Inv. gamma	0.01	0.05	0.007	0.0067	0.005:0.008

Table 3: Prior and Posterior Distribution of Estimated Exogenous Shock Processes

3.4. Historical Variance Decomposition

After completing the model parametrization, we analyse its properties in terms of responses to standard shocks²⁰ and its ability to represent and identify the fluctuations in the historical data.

Estimating the model with real data allows to conduct a historical variance decomposition. The variance decomposition assesses the importance of different shocks by determining the relative share of variance that each structural shock contributes to the total variance of each variable. Figures (2)-(6) visualize the variance decomposition for the following variables: real consumption, interest rates charged on mortgages, real house prices, real investment, and interest rates charged for corporate loans.

In Figure (2) the variance decomposition of consumption shows that the model identifies the productivity shock and the shock to idiosyncratic risk in mortgage lending to be the main drivers of the build-up and fall in real consumption during the Great Recession. The main channel through which the *shock to idiosyncratic risk of mortgages* can have a procyclical effect on consumption is through lending and house prices. Figure (3) demonstrates that this idiosyncratic risk shock contributed negatively to mortgages interest rates in the build up phase, and positively in the crash period. Figure (4) shows that the same shock contributed positively to house prices in the build up phase, and negatively in the crash period.

The variance decomposition of investment indicates that the dynamics of real investment can be well explained by shocks to idiosyncratic firm default risk, refer to Figure (5). The channel works as follows: A lower firm idiosyncratic default risk shock leads to lower expected default rates of firm loans, and hence lower interest rates as shown in Figure (6). Lower interest rates lead to higher investment.

In summary, the model is able to identify both the build up-phase and the crash of the recent crisis as originating from mortgage and firm lending. In the build up phase, lower mortgage risk leads to lower mortgage interest rates, higher house prices, and higher consumption. At the same time, a lower firm lending risk leads to lower firm interest rates and higher investment. The 2008 crash is explained as a rapid increase in the risk of both types of lending (mortgages and firm loans) leading to higher interest rate spreads, and a decline in both types of borrowing and house prices. As a result consumption, investment and output all decline.

The results of the variance decomposition motivate the comparison of the effectiveness of different policy instruments to

²⁰See Appendix 8.2 for comparison of the responses of the parametrized model to the related models in the literature.

set risk-weights during a crisis scenario. In particular, we simulate the crisis as originating from a shock to the idiosyncratic risk in the mortgage market.

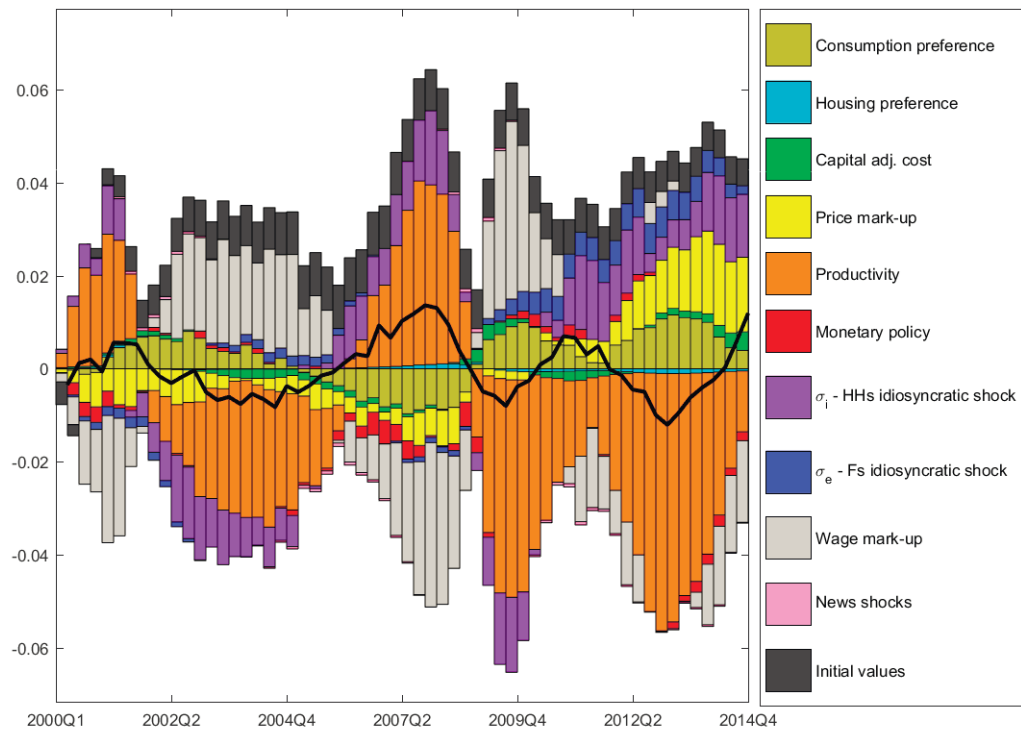


Figure 2: Variance decomposition - Real consumption

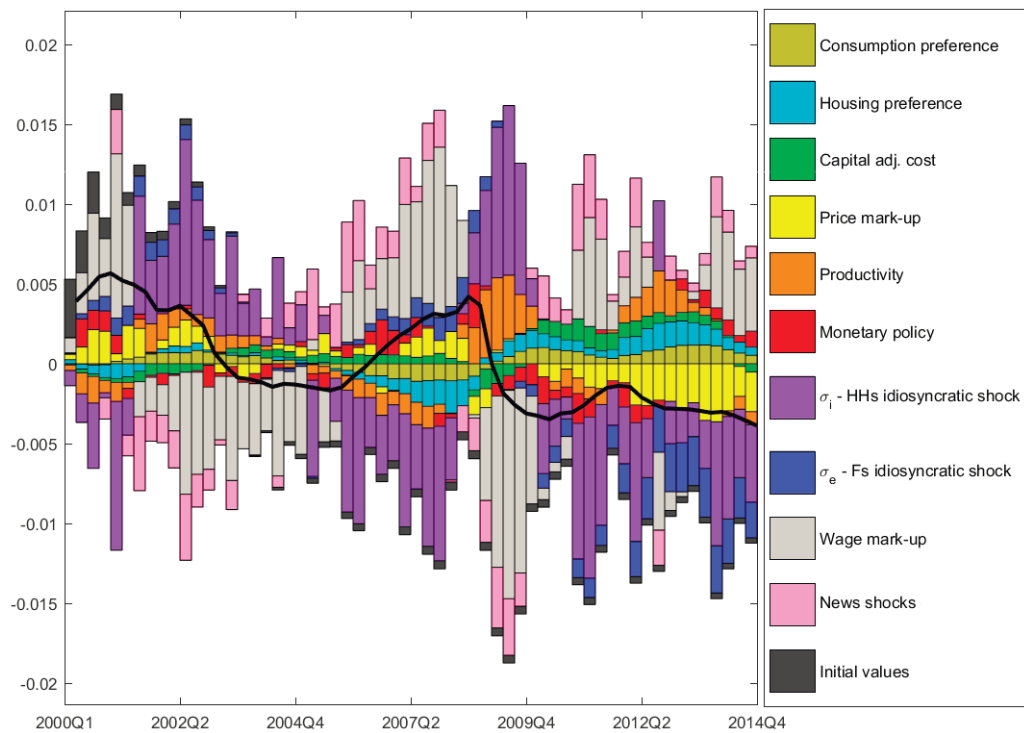


Figure 3: Variance decomposition - Interest rate - Households

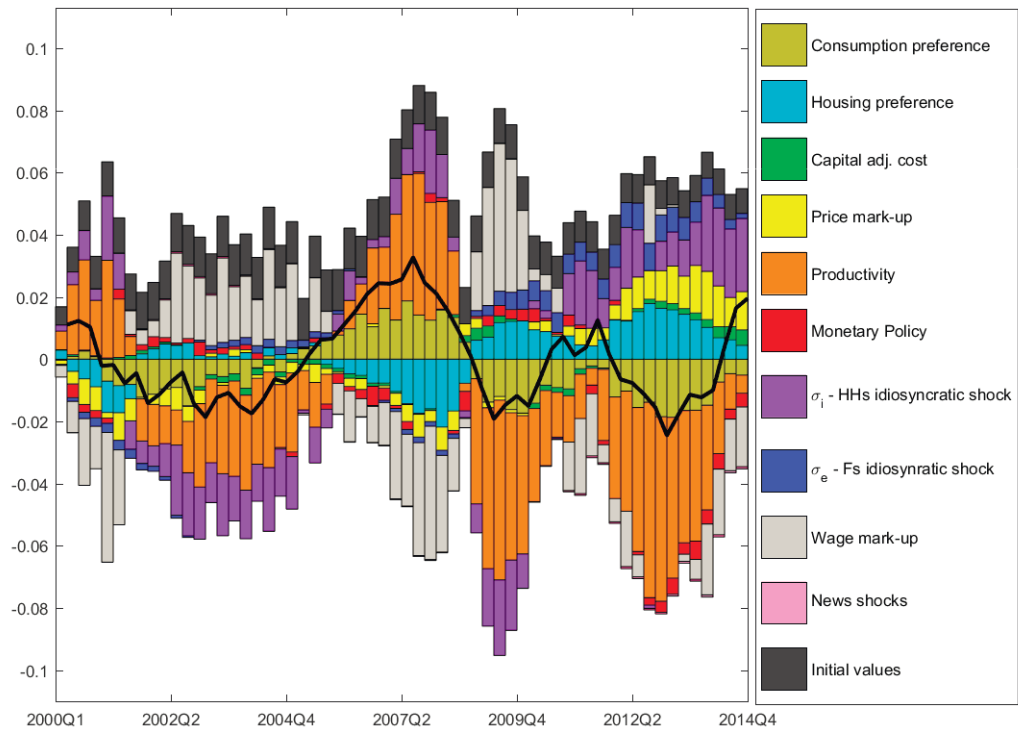


Figure 4: Variance decomposition - Real house prices

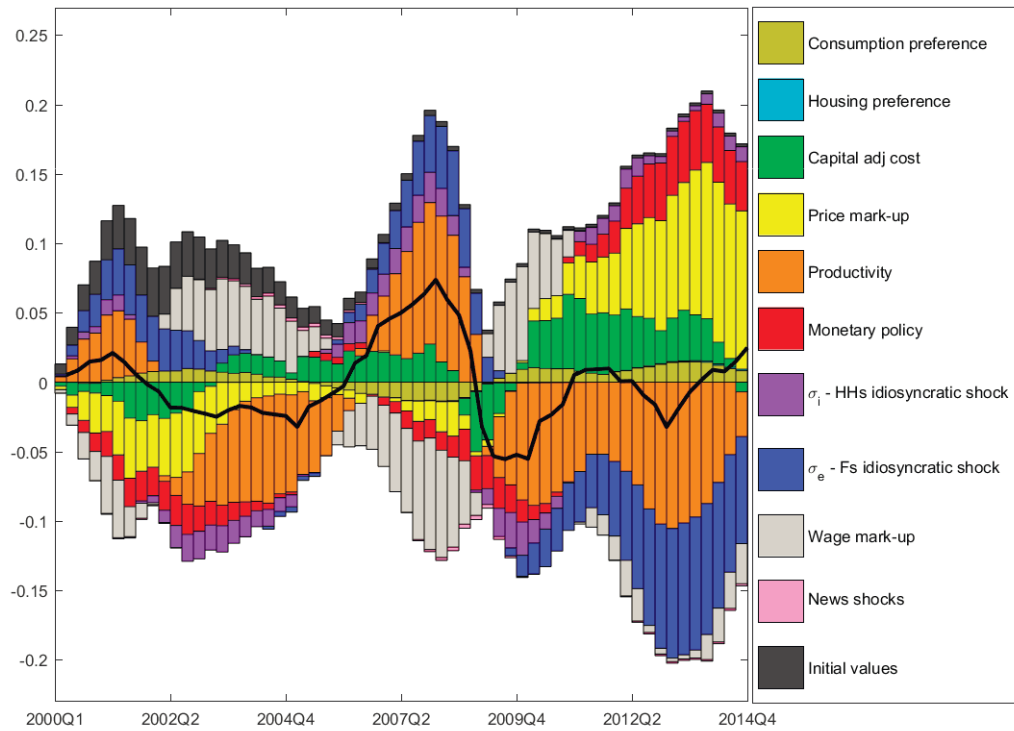


Figure 5: Variance decomposition - Real investment

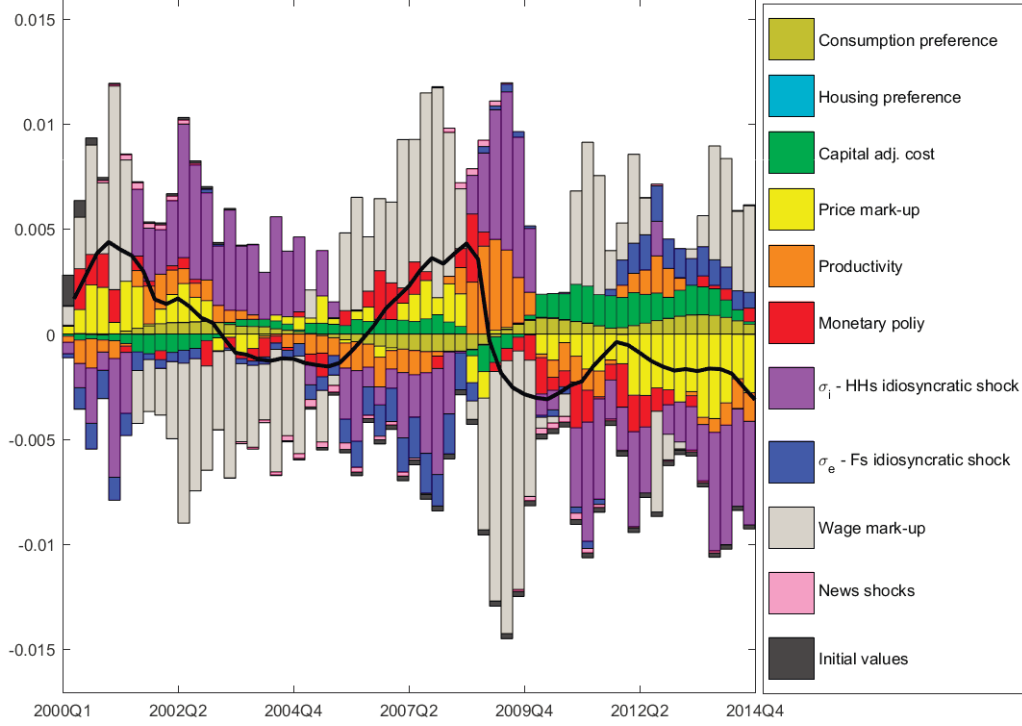


Figure 6: Variance decomposition - Interest rate - Firms

4. Policy analysis

In this section, we analyse and compare three alternative risk-weight setting policies. First, the leverage ratio in subsection 4.1. Second, the internal ratings-based (IRB) approach which was introduced by Basel II in subsection 4.2. And finally a novel sectoral macroprudential risk-weight setting rule in subsection 4.3. The impacts of the three policy settings and their effectiveness in stabilizing the economy are compared under two different scenarios, in subsections 4.4 and 4.5 respectively. The first scenario represents the crash phase of the crisis, and the second consists of a simulated boom and bust cycle. Section 4.6. shows the model behaviour for a variety of different types of shocks. Our conclusions that the macroprudential rule performs best in smoothing the business cycle are robust to loan supply shocks, monetary policy shocks, technology shocks, and shocks to entrepreneurs' idiosyncratic risk. In section 4.7., we replicate the study using alternative parameter values within our macroprudential approach.²¹ The alternative parameter values we have used for our macroprudential approach are those that maximize social welfare, and that correspond to an optimal macroprudential rule.

4.1. The Leverage Ratio

The related literature that seeks to analyse the effects of macroprudential capital requirements in general equilibrium models generally regards the regulatory capital requirement as a leverage ratio, thereby abstracting from any risk-weighting of assets.²² Such a setup is equivalent to our leverage ratio case in which the risk-weights are constant and equal to one, i.e. $w_t^I = w_t^F = 1$. Hence in our model and in the case of the leverage ratio, the 'risk-weighted assets' in equation (2.7) equal the total assets of

²¹Recall that under the leverage ratio the risk-weights are static and equal to one, while the risk-weights under the IRB approach are set according to observed historical PDs and LGDs. Therefore, under both the leverage ratio and the IRB cases - there was no discretion on our parameter choice within our modeling approach.

²²For example, see [Angelini et al. \(2014\)](#) and [Gerali et al. \(2010\)](#).

the bank, $RWA_t^{LR} = B_t^I + B_t^E$. Under the policy of the leverage ratio, it follows that the lending interest rate spreads are determined by the deviation of the capital-asset ratio $\frac{K_t^b}{B_t^I + B_t^E}$ from the requirement ν^b in equation (2.8).

4.2. The Internal ratings-based (IRB) risk-weighting

Large banks ($> EUR\ 100bn$ in assets) generally calculate their risk-weighted assets following the Internal ratings-based (IRB) approach.²³ In contrast to papers such as Angelini et al. (2014) and Gerali et al. (2010), our model allows for risky defaulting loans and hence can be used as a means to study the impact of the IRB approach on the real economy.

The purpose of the IRB framework is to guarantee financial stability by imposing a bank capital requirement that is sufficient to absorb any unexpected losses arising from the assets of a bank. The capital charge that the bank has to hold for each loan type is proportional to the loan's probability of incurring unexpected losses. Below, we discuss the IRB approach in detail and then apply it to our theoretical model presented in section 3.

According to the IRB approach, expected losses (EL) should be covered by bank provisions and are entered on the bank's balance sheet directly as a cost associated with its lending. In the model, bank provisioning is represented by the retail level of the banking system. Retail bankers set the interest rate spread by taking into account the probability of default. Unexpected losses (UL) arise in exceptional circumstances and hence are not taken into account by bank provisioning at the retail branch level. In the model, the unexpected losses are taken into account at the wholesale level of the banking system. The wholesale branch makes sure that the capital-asset requirement is met, i.e. assets that are more volatile / more prone to generating unexpected losses require the bank to hold more capital to absorb those unexpected losses.

The IRB framework allows banks to calculate the risk-weight of a specific loan type in order to ensure it has enough capital to cover the unexpected loss region shown in Figure (7). The expected loss (EL) per unit of a loan is defined as the expected annual probability of default (PD) times the loss-given-default (LGD), $EL = PD \cdot LGD$. The expected total losses ($TL = EL + UL$) are rather higher than the pure EL, as some unexpected losses (UL) are also likely to occur in some scenarios where systematic factors (e.g. large economy-wide recessions) make the realised annual default rate higher than the expected PD. To model the UL, and thereby derive capital requirements, one must therefore condition the PD and LGD to increase them beyond their simple historical average levels. In the IRB approach, the conditioning of the PD is designed to increase the unconditioned PD to the point where the bank is able to absorb the unexpected losses on its assets in all but the absolute most severe (top 0.1%) negative scenarios that may occur in the following year.

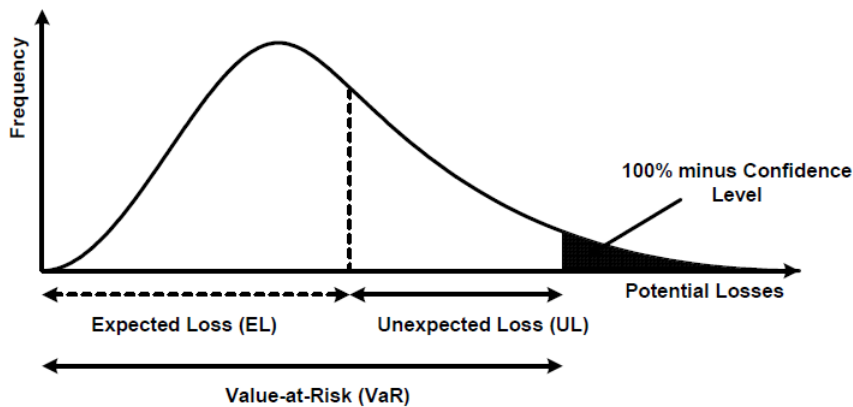


Figure 7: Loss distribution of a loan portfolio

²³The current Basel reform introduces both, a leverage ratio and asset risk-weight-based constraints on bank capital.

Unexpected losses can be expressed as

$$UL = TL - EL = LGD^c \cdot PD^c - PD \cdot LGD \quad (4.1)$$

where PD^c denotes the conditional probability of default and LGD^c the conditional loss-given-default. Hence, the risk-weight that would ensure enough capital to cover the unexpected losses of loan type j can be calculated as

$$w_t^j = \frac{1}{\nu^b} UL_t^j \quad (4.2)$$

where ν^b is the regulatory risk-weighted capital-asset ratio requirement. As a result, the risk-weight of a particular loan type becomes a function of the respective default probability PD and loss-given-default LGD.

In our theoretical model, we are able to use the true model values for the PD and LGD, thus eliminating any estimation errors. In terms of our notation, the PD is simply $F_t^{j,a}$ and the expected loss in the event of default of loan type j is given by

$$EL_t^j = \frac{r_t^j F(\bar{\omega}_t^{j,a}, \sigma_\omega^j)}{\pi_{t+1}} - \frac{(1 - \mu^j) G(\bar{\omega}_t^{j,a}, \sigma_\omega^j) q_{t+1}^j H_t^j}{B_t^j} \quad (4.3)$$

The expected losses in (4.3) are expressed as the value of foregone interest minus the value of repossessed collateral. We calculate the loss-given-default as $LGD = \frac{EL}{PD}$, and the conditional PD^c , and LGD^c values according to the Basel methodology.²⁴ Using the latter we calculate the total losses as $TL = LGD^c \cdot PD^c$. Using equation (4.1), we compute the loan specific, time varying risk-weight according to equation (4.2).

4.3. Macprudential risk-weighting

The IRB risk-weight setting approach presented in the previous section creates a positive relationship between the risk-weight of a particular type of loan and its probability of default which makes risk-weights procyclical. For example, in the boom phase of the economy, asset prices are high, and lending conditions are lax, hence the default probability of loans decreases, leading to lower risk-weights. Similarly, in the downturn, asset prices are low, and lending conditions tighten, the default rate of loans increases leading to higher risk-weights. In both phases of the credit cycle, the IRB approach may result in risk-weights that reinforce economic fluctuations thereby increasing financial fragility. This procyclicality of the IRB capital requirement is consistent with the empirical evidence found by Behn et al. (2014) and Goodhart et al. (2004).

As an alternative policy setting, we propose macroprudential interventions that aim to attenuate the business cycle and minimize its vulnerability to financial distress.²⁵ For this purpose, we employ a Taylor-type rule that sets the risk-weight of a loan type responding to an indicator. We have chosen the indicator following the regulatory guidelines and set our instruments to respond to credit-to-GDP measures (ESRB, 2014). Therefore, in our macroprudential setting, we substitute the risk-weights of equation (4.2) with the following Taylor-type rule

$$w_t^j = (\bar{w}^j)^{(1-\rho_w)} (w_{t-1}^j)^{\rho_w} \left(\frac{B_t^j/Y_t}{\bar{B}^j/\bar{Y}} \right)^{\chi_w(1-\rho_w)} \quad (4.4)$$

²⁴See BCBS (2005), for the LGD^c we use the unconditional LDG increased by 10% as a downturn estimate.

²⁵From a legal policy perspective, such a macroprudential intervention would be feasible according to the Capital Requirements Regulation (CRR IV) which allows for the regulatory setting of higher risk-weights due to "financial stability considerations", see Article 124(4)(b).

The risk-weight of loans to households and firms are set according to the deviation of the loan-specific measure of leverage (B_t^j/Y_t) from its steady state, where the parameters χ_w and ρ_w represent the responsiveness of the instrument to the leverage measure and its autoregressive properties, respectively.

In the following sections of the crisis simulations, we use countercyclical²⁶ values for the parameters governing the responsiveness of the macroprudential rule to leverage that lead to a realistic response of policymakers to credit indicators in terms of instrument volatility.²⁷ In the appendix (8.5), we present the same responses with an optimal rule in which the parameters are set so as to maximize social welfare but lead to more volatile instruments.²⁸ We refrain from using optimal MaP policy rule in our main simulations, firstly because it leads to unrealistically volatile policy instruments and second since it has clear welfare advantage over the other settings that represent static policy and policy pinned down by the IRB regulation. Moreover, optimal policy in terms of social welfare is not the main goal of this paper which focuses on comparing the current approach in the literature with the imposed regulation and a proposed alternative setting of risk-weights.

In the subsequent two sections, we compare and analyse the different policy settings regarding their effectiveness in stabilizing the economy. First, during a bust phase scenario, and second during a boom-bust cycle of a crisis scenario.

4.4. Analysis in the crisis scenario - Bust Phase

This scenario allows us to represent the crash phase of the crisis and is therefore suitable to assess different policies regarding their effect in the aftermath of a crisis. We study the impulse responses to an unexpected increase in the standard deviation of the idiosyncratic shock to mortgages. In Section 3.4, the variance decomposition identified this shock to be a driving factor at the peak of the crisis. The direct impact of this shock consists of increasing the proportion of loans below the ex-ante default threshold. This leads to a larger default rate for mortgages than was expected by the banks when the loans were issued. This in turn leads to losses to banks and the destruction of bank capital resulting in the capital-asset ratio falling below the regulatory requirement.

Figures (8) and (9) highlight the differences in the impulse responses to the shock due to the different policy settings of capital requirements.²⁹ In the leverage ratio (LR) case (static and equal risk-weights, both equal to one), the destruction of bank capital reduces the capital-asset ratio and the capital to risk-weighted asset ratio below the regulatory requirements. In order to adjust their balance sheet to ensure the regulatory requirement is met, banks increase the wholesale interest rate spread, thereby leading to higher interest rates on loans. The higher interest rates depress economic activity and lead to a long recession.

In contrast to the leverage ratio case, the IRB approach increases the risk-weights of mortgages as the estimate of default probability increases. The risk-weights decrease following the process of household deleveraging (which results in the default probability falling). The higher risk-weight on mortgages leads to a higher value for the risk-weighted assets (RWAs) on the mortgage book in comparison to the other policies. This in turn leads to a larger decline in the Capital/RWA measure and hence to a higher increase in spreads and interest rates. Ultimately, this results in a larger decline in investment and output following the shock, and a slower recovery compared to the leverage ratio (LR) case.

²⁶We refer to countercyclical setting in the sense of countercyclical capital requirements which are achieved through procyclical risk-weights and a positive value for the parameter χ_w .

²⁷Employed parameter values: $\rho_w = 0.1103$ and $\chi_w = 1.9483$.

²⁸Optimal parameter values: $\rho_w = -0.2023$ and $\chi_w = 4.9587$. The stepwise welfare optimization routine also indicates that a wide range of countercyclical values for the parameters lead to smoothing of the business cycle.

²⁹Figures (8) and (9) shows the responses of the variables in percentage deviation from steady-state values ($\ln(X/\bar{X})$) except for the responses of variables denoted with a star *. These variables are plotted as absolute deviations ($X - \bar{X}$) due to different steady states or variables already being in percentage form.

Finally, the macroprudential approach to setting risk-weights has a countercyclical effect as it decreases the risk-weights on both types of lending as a result of the de-risking effect of the lower sectoral leverage levels in the bust phase of the crisis. This leads to lower risk-weighted assets (RWA) and a higher Capital/RWA ratio, and thereby to a relatively lower increase in spreads and interest rates on bank lending. Ultimately, this results in the stimulation of investment and thereby to a relatively fast recovery of output and investment - compared to the leverage ratio (LR) case and the IRB approach.

In summary, our macroprudential approach to setting risk-weights is best suited to mitigating the banking sector's tendency to amplify the recession. In terms of relative empirical magnitude of the results, in the bust scenario the IRB approach leads to a decline in output that is - at the point of maximum difference - almost twice as large as is observed under the macroprudential approach. This larger drop in output in the IRB case is driven mainly by investment declining by an additional third in the IRB case over and above the decline in the macroprudential case.³⁰

For robustness purposes, we replicate the study using alternative parameter values within our macroprudential approach. Recall that under the leverage ratio the risk-weights are static and equal to one, while the risk-weights under the IRB approach are set according to observed historical PDs and LGDs. Therefore, under both the leverage ratio and the IRB cases - there was no discretion on our parameter choice within our modeling approach.

The alternative parameter values we have used for our macroprudential approach are those that maximize social welfare, and that correspond to an optimal macroprudential policy rule (discussed in detail in section 4.3). This optimal macroprudential policy rule reacts more strongly to changes in sectoral leverage - and thereby attenuates sectoral credit booms more aggressively.³¹ The results show that alternative parameter choices do not alter our conclusions. The macroprudential approach always performs best in reducing the banking sector's tendency to amplify the business cycle.

³⁰Note that we are comparing the relative magnitude of the deviations as they are plotted - in percentage terms.

³¹See appendix (8.5).

Figure 8: IRF - unexpected shock to σ^i

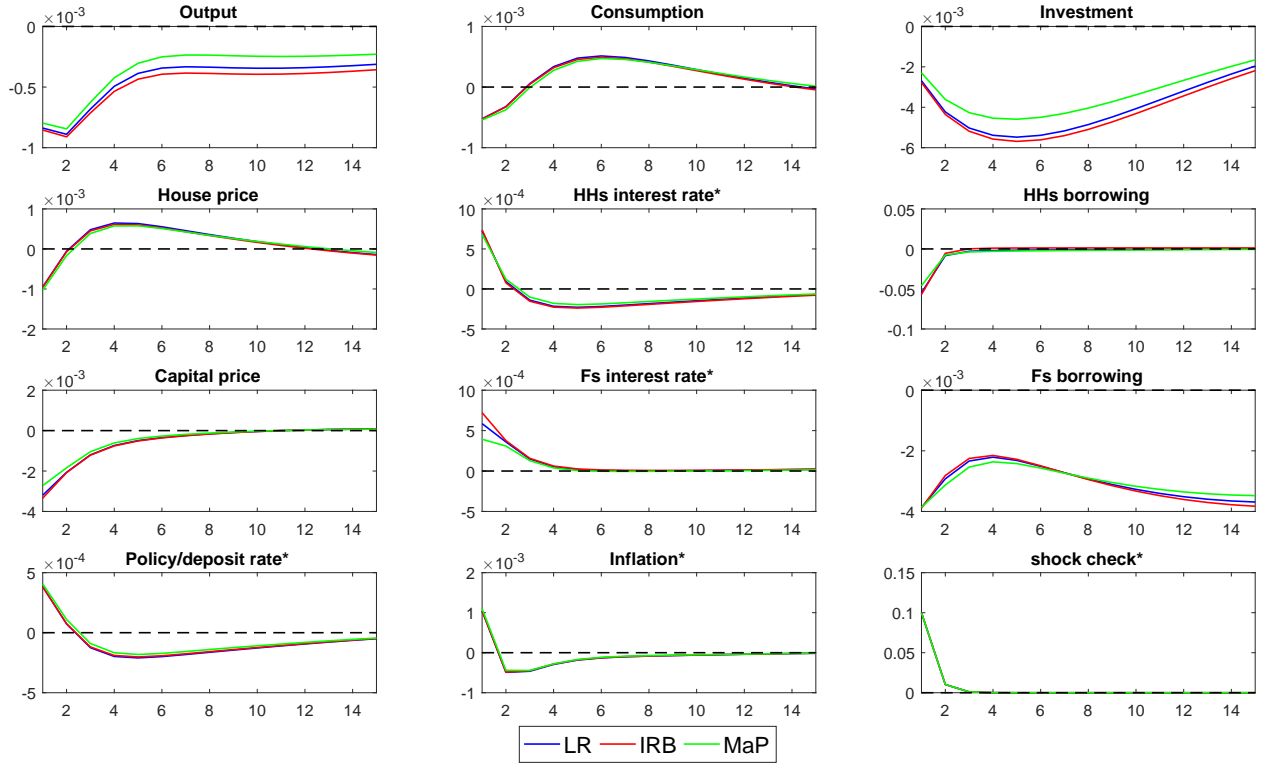
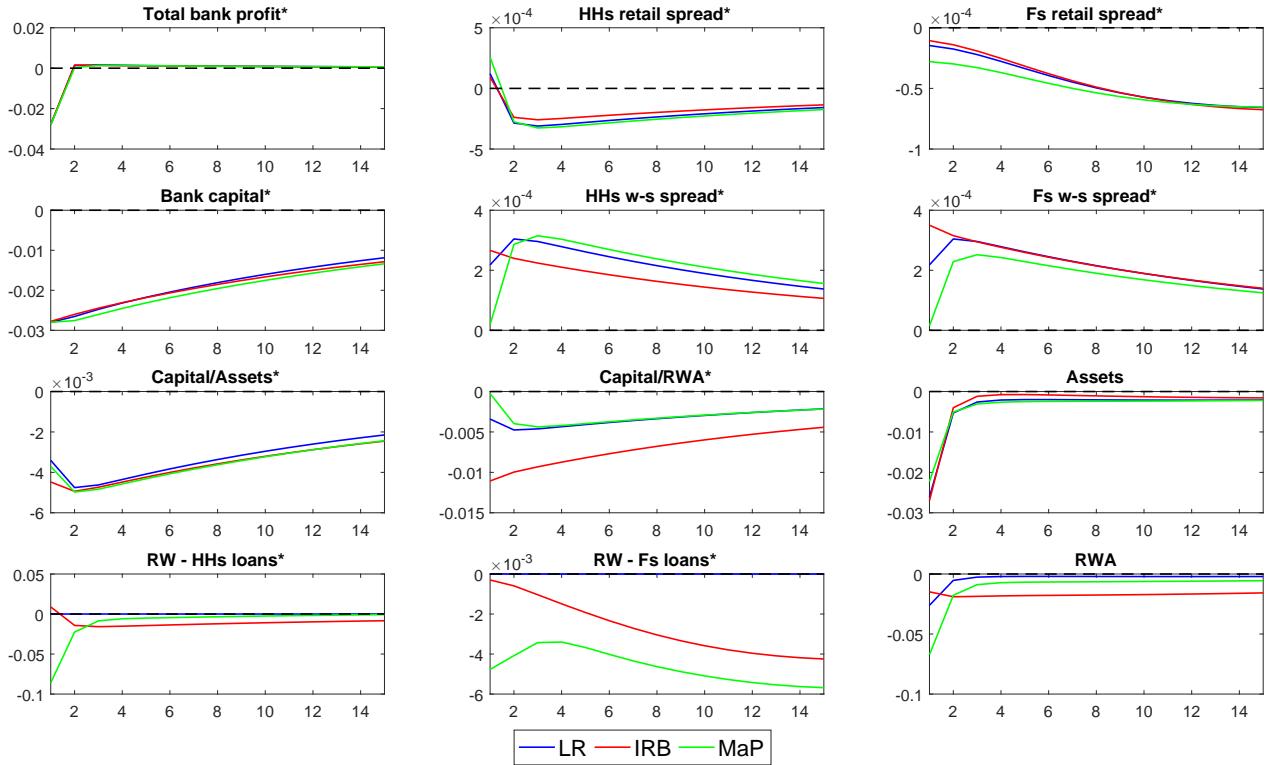


Figure 9: IRF - unexpected shock to σ^i



4.5. Analysis in the crisis scenario - Boom and Bust

In this crisis scenario, we aim to represent both the build-up and crash phases of the crisis and thus to examine how the different policy approaches perform in terms of their amplifying or attenuating effects on the boom phase of the cycle. The scenario is simulated as a positive news shock in the initial period whereby the agents in the economy expect the default rate of mortgages four periods in the future to be lower than before the shock. This leads to optimism and buoyancy in both lending and asset markets. However, when period 4 arrives, the shock does not occur, and agents' expectations of lower default rates do not materialize. As a result, the default rate of mortgages is higher than expected, and banks realize losses thereby leading to a destruction of bank capital.

Figures (10) and (11) show the various impacts on agents' behaviour associated with the positive news shock. In the leverage ratio case (static and equal risk-weights, both equal to one), optimism leads to higher borrowing and decreases in the Capital-Assets and Capital-Risk-weighted-Assets ratios. Banks respond to these decreased regulatory capital ratios by increasing the wholesale spread to stay in line with the regulatory requirement. However, the higher wholesale spread to mortgages is not enough to offset the lower retail spread which is driven by the lower default probability in the boom phase. As a result, mortgages face lower interest rates, and sectoral leverage is increased further.

Unlike the results of the leverage ratio (LR) case, the IRB approach results in decreases to the risk-weights on loans due to lower PD estimates in the optimistic phase. As a result, risk-weighted assets (RWA) decline and the Capital/RWA measure increases leaving the impression that banks are better capitalised when, in reality, the pure Capital/Asset measure has decreased. During this phase, IRB banks decrease their wholesale spreads and further reinforce lower interest rates and higher sectoral leverage.

As in the previous scenario, the macroprudential approach to setting risk-weights has a countercyclical effect during the boom phase of the crisis as it increases risk-weights on both types of lending in response to the increases in leverage in both sectors. This leads to higher risk-weighted assets (RWA) and a lower Capital/RWA ratio - and hence to an increase in wholesale spreads, leading to higher interest rates and lower borrowing than is observed under the other capital measurement approaches.

At period four the positive shock does not materialize, and the economy faces less favourable financial conditions than expected. From that point forward, the crisis proceeds in a similar way to the bust phase in section 5.3. The difference between the scenarios is that the negative shock here is driven by unmaterialized expectations rather than actual changes in financial outcomes.³²

In the leverage ratio setting, the destruction of bank capital reduces the Capital/Assets and Capital/RWA ratios below the regulatory requirement. In order to meet their regulatory requirement, banks increase wholesale spreads resulting in higher interest rates on loans. The higher rates depress economic activity and lead to a relatively long recession.

Unlike the leverage ratio (LR) case, the IRB approach increases the risk-weight on mortgages at the point where the negative shock arises due to higher resulting estimates of PDs. Subsequently, risk-weights then fall as households deleverage, and PDs decline. The higher risk-weight on mortgages leads to a larger increase in the risk-weighted assets associated with banks' mortgage books in comparison to the other policies. In turn, this leads to a larger decline of the Capital/RWA ratio and hence to a greater increase in spreads and interest rates on lending. Output, consumption, and investment adjust less quickly. Overall, the economy ends up recovering slower under the IRB approach compared to leverage ratio (LR) regulation.

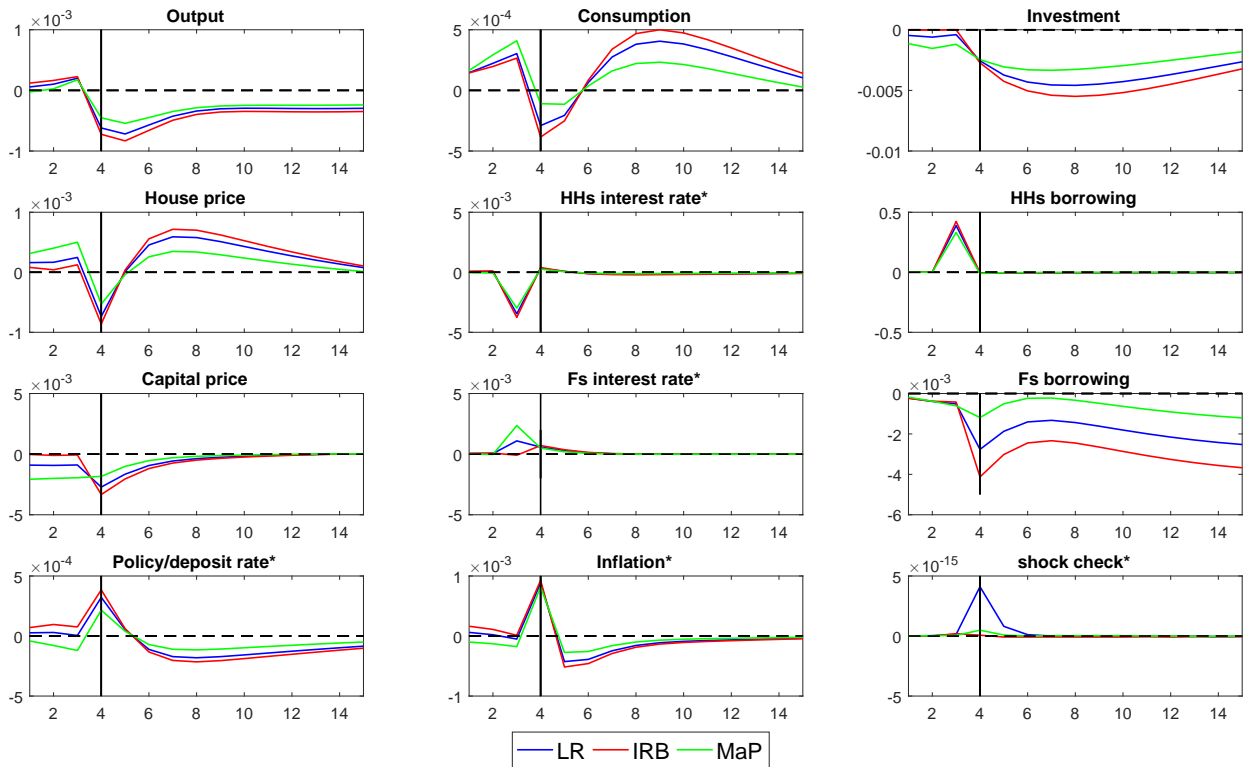
In the case of our macroprudential approach to setting risk-weights, lending conditions on mortgages are tight before the

³²Note that in the unrealized news shock (boom and bust) scenario the dynamics are entirely driven by expectations while the impulse response of the shock remains flat.

shock as capital requirements have become stricter as leverage in the housing sector increased. The destruction of bank capital is therefore lower when the shock hits, and the negative impacts of the shock are also lower. After the shock, the economy faces relatively favourable credit conditions in comparison to the IRB and leverage ratio regulatory cases - and the economic recovery is therefore faster, as investment can be sustained through the cycle. Finally, reflecting on the observed persistent reduction in firm borrowing we can note that although that the magnitude is much smaller than households' borrowing, the former seems to be driven by slow recovery of investment. However, note that under the more responsive optimal macroprudential policy setting, firms borrowing is able to recover faster - figure 24.

In summary, our sectoral macroprudential approach to setting risk-weights is best suited to mitigating the banking sector's tendency to amplify the business cycle. In the boom-bust crisis scenario, the differences between the relative empirical magnitudes of the results are also striking. At the point of maximum difference, output again declines almost twice as much in response to the bust under the IRB approach in comparison to the macroprudential approach. The difference in output is mainly driven by consumption falling more than twice as deep under the IRB approach in comparison to the macroprudential approach. The difference in output is mainly driven by consumption falling more than twice as deep under the IRB approach in comparison to the macroprudential approach.³³ As in our approach for the bust scenario, for robustness purposes we replicate the study using alternative parameter values within our sectoral macroprudential approach. Again, the results obtained from the alternative parameter sets do not alter our conclusions.³⁴

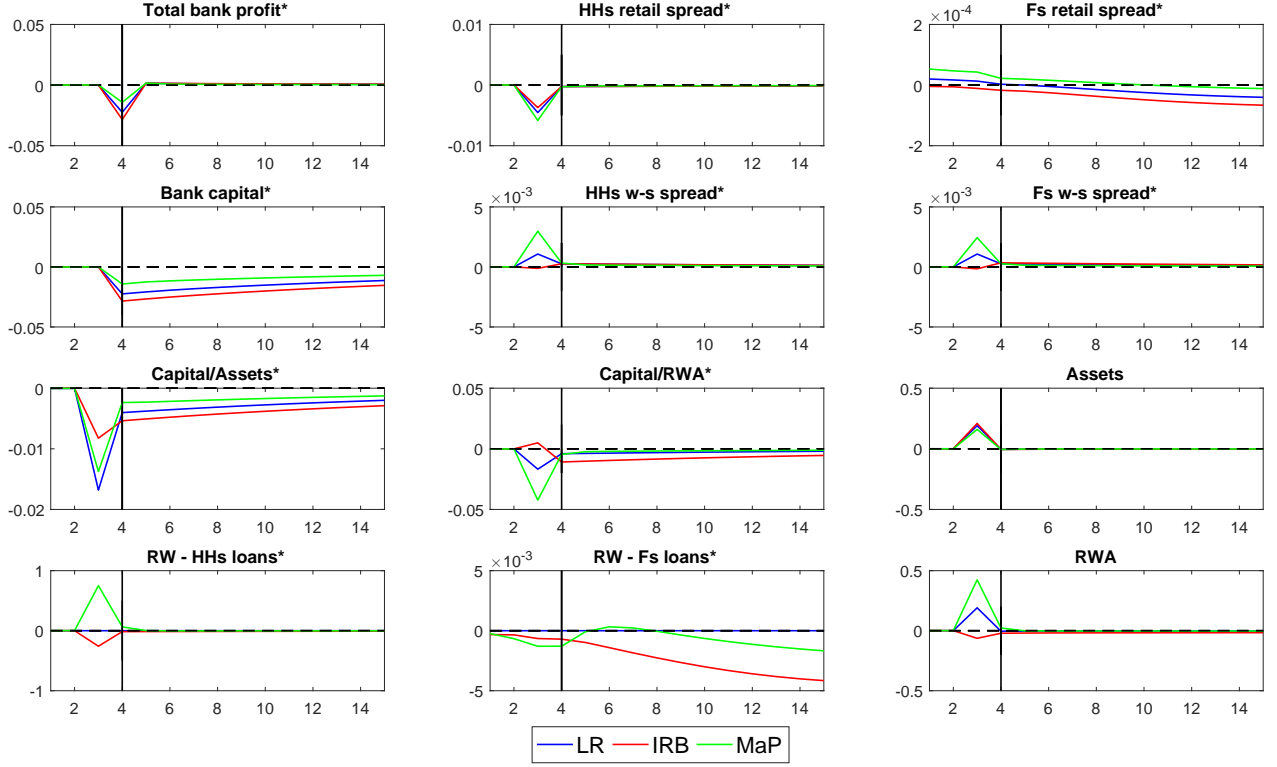
Figure 10: IRF - unrealized news shock to σ^i at period 4



³³Note that we are comparing the relative magnitude of the deviations as they are plotted - in percentage terms.

³⁴See appendix (8.5).

Figure 11: IRF - unrealized news shock to σ^i at period 4



4.6. Alternative Crisis Scenarios and Shocks

In the previous sections, we simulated a financial crisis originating from mortgage lending thereby capturing a scenario that is similar to the Great Recession. In this section, we analyse scenarios where the downturn originates either from a shock to corporate lending, or from an exogenous bank crisis. We also outline the results of simulations involving shocks to technology and monetary policy.

4.6.1. Firm lending shock

Following the estimation results in table 3, the idiosyncratic shock to firm loans was found to have a smaller standard deviation (σ_{σ_e}) and higher persistence (ρ_{σ_e}), compared to our main simulations using a shock to household loans. The impulse responses therefore have lower magnitude and greater persistence in comparison to our main simulation. The impulse response figures for the firm lending shock are shown in appendix C, section 8.3.

The direct impact of this shock is to increase the proportion of loans that fall below the ex-ante default threshold. This leads to a larger default rate for firms than was expected by the banks when the loans were issued. In turn, this leads to bank losses, to the (endogenous) destruction of bank capital, and to the capital-asset ratio falling below the regulatory requirement. The results are very similar to our main simulation. Firm lending becomes riskier, to which the IRB approach responds with higher risk-weights and further tightening of lending. In contrast, the macroprudential approach decreases the risk-weights thus stimulating firm borrowing, investment, and thereby supporting a quicker recovery.

4.6.2. Bank capital destruction shock

The modelling of exogenous bank capital destruction shocks is common in the literature, in particular where risky lending is not captured. By contrast, our model allows for risky lending thereby facilitating the simulation of endogenous bank capital destruction (e.g. refer to our main shock and the firm lending shock). Nonetheless, we also simulate the results of an exogenous bank capital destruction shock with the impulse response figures presented in appendix C, section 8.4.³⁵ The exogenous destruction of bank capital leads to a lower regulatory ratio, leading the bank to tighten its lending in order to repair its balance sheet. The results are similar to the other crisis scenarios with the macroprudential rule being able to mitigate the shock through lower risk-weights and lower absolute capital requirements for banks.

4.6.3. Technology and Monetary shocks

The results of the model simulations of standard technology and monetary policy shocks are shown in appendix C, section 8.2.³⁶ We highlight one interesting observation on the interaction of monetary policy and our macroprudential rule: during the monetary tightening, the macroprudential setting relaxes risk-weights and as a result lowers absolute capital requirements. This reduces the negative impact of a monetary policy shock on investment thereby smoothing the cycle. Hence, the macroprudential rule mitigates the negative impact of a monetary tightening and hence helps to smooth the cycle. The macroprudential rule could therefore somewhat offset the ability of monetary policy to influence economic activity via the bank lending channel. This could be a potential drawback of imposing the macroprudential rule given that it is desirable to maintain the bank lending channel for monetary transmission. Further analysis of the interaction between the macroprudential rule and monetary policy could be an interesting line for our future research.

It is finally noted that none of the simulations have any quantitative meaning in *absolute* terms.³⁷ As in the case of Gerali et al. (2010), our results are instead appropriate to highlight the *relative* impacts of the different policy settings. These relative results, and the insights on the underlying mechanisms behind these relative results provide insights for the design of future bank regulation and of macroprudential policy.

4.7. Procyclicality and Welfare

In the previous sections, we compared the responses of the three different policy settings in two different crisis scenarios which represent closely the 2008 financial crisis. In order to represent the ability of the different policy settings to smoothen or amplify the business cycle under various shocks, we report the variation of the main macroeconomic variables' volatility under each capital policy instrument based on the variables' theoretical moments.³⁸ In addition, we report the resulting social welfare in terms of lifetime utility in each of these policy settings.

The welfare of each agent $j = \{P, I, E\}$ is given by the expected discounted sum of lifetime utility:

$$\Omega_t^j = \max E_t \left[\sum_{i=0}^{\infty} (\beta^j)^i U(C_{t+i}^j, H_{t+i}^j, L_{t+i}^j) \right] \quad (4.5)$$

³⁵The shock is of magnitude of one standard deviation which is set as in Gerali et al. (2010), $\sigma_{K^b} = 0.03$

³⁶In the appendix, we also discuss and compare our results with Gerali et al. (2010) as a closely related model.

³⁷The linearised framework that we employ does not allow for accurate representation of large shocks which lead to large deviations from the steady state.

³⁸The computed theoretical moments are equivalent to a sufficiently long run simulation with all possible shocks being active.

which at the optimum has the following Bellman form:

$$\Omega_t^j = U(C_t^j, H_t^j, L_t^j) + \beta^j \Omega_{t+1}^j \quad (4.6)$$

Finally, we compute an optimal sectoral macroprudential rule by setting the coefficients of the sectoral macroprudential policy rule to maximize the sum of all agent's welfares in our model. In doing so, we study the ex-ante optimal macroprudential policy rule based on the second-order approximated solution of the model. We also compute the welfare implied by the different policy rules conditional on the initial state being the deterministic steady-state. We compare the optimal macroprudential policy rule that maximizes social welfare with the baseline macroprudential policy rule, the leverage ratio and the IRB risk-weight setting. We do so in two ways: First in terms welfare levels and second with the consumption-equivalent (CE) measure - calculated as the percentage increase in steady-state consumption that would make welfare under the leverage ratio static policy setting equal to welfare under each of the settings.

Table (4) reports the results showing that relatively to the static policy setting of the leverage ratio, the IRB risk-weights setting leads to a higher variation in the macroeconomic variables and lower social welfare. On the other hand, the macroprudential rule smoothens the business cycle by decreasing the variation in the macroeconomic variables and leads to higher social welfare. Finally, the optimal macroprudential rule leads to higher responsiveness of the risk-weights to leverage: $\chi_w = 4.9587$ compared to the baseline macroprudential rule with $\chi_w = 1.9483$. Overall, the results point to significant macroeconomic stabilization gains from employing a sectoral risk-weighting approach - in comparison to the IRB approach or the leverage ratio. However, the extreme responsiveness of the optimal macroprudential rule might be unrealistic from a policy perspective. In reality, policy-makers do not have access to perfect real-time information, and other decision-making frictions are often in place. For this reason, we use the macroprudential rule with the lower responsiveness for our main simulations. We report all impulse responses using the optimal macroprudential risk-weight setting in the appendix (8.5).

Risk-weight setting policy	Standard Deviation				Welfare	Cons. Equiv.
	Income	Cons.	Invest.	Borrowing	Wel	CE
Leverage Ratio	0.1101	0.0901	0.0298	0.9615	-347.07	0%
IRB	0.1105	0.0903	0.0306	0.9602	-351.94	-1.98%
Macroprudential $\rho_w = 0.1103$ $\chi_w = 1.9483$	0.1096	0.0899	0.0276	0.8844	-345.62	0.59%
Opt Macroprudential $\rho_w = -0.2023$ $\chi_w = 4.9587$	0.1094	0.0897	0.0270	0.7662	-344.04	1.23%

Table 4: Risk-Weight Setting Policies and the Volatility of Target Variables and Welfare

5. Conclusion

This paper investigates the implications of different methods for setting bank capital requirements on the financial cycle and the macroeconomy. Three different approaches are tested. The Leverage Ratio (LR) approach keeps risk-weights static through the cycle. The Internal Ratings Based approach (IRB) sets risk-weights for each asset on the basis of estimates of for PDs and LGDs. Alternatively, our macroprudential approach sets risk-weights for each asset type in a countercyclical manner - inversely linking risk-weights to measures of leverage in each sector. We compare these three methods for setting capital requirements in terms of their response to a crisis originating from mortgage lending.

Our results show that in both boom and bust phases of the crisis the IRB approach leads to procyclical capital requirements. In the boom phase, the IRB approach leads to looser capital requirements and thereby to lending conditions that reinforce market exuberance. In the bust phase, higher PD estimates lead to higher risk-weights and tighter capital requirements that depress bank lending and push down on economic activity. The IRB approach therefore tends to amplify the financial cycle in the event of a housing crisis.

The leverage ratio policy is less procyclical than the IRB approach, but does nothing to counteract the cycle meaning that the mortgage shock is still strongly transmitted through the banking system into the real economy. By contrast, our macroprudential approach to setting risk-weights leads to countercyclicality in capital requirements in both the boom and bust phases of the crisis thereby serving to attenuate the financial cycle. The negative impact of the financial crash to the real economy is smaller, and the recovery happens faster.

Our results highlight the relative effectiveness of the three policy settings in providing stable financing, and smoothing the business cycle. In addition, our model provides a basis for understanding the mechanisms underlying our conclusions. The simulations have no quantitative meaning in absolute terms. However, the model captures social welfare and it is possible to quantitatively compare the social welfare implications of each regulatory approach. Using the Leverage Ratio (LR) as a baseline, the IRB approach leads to a 1.4% decrease in welfare, whereas the macroprudential approach leads to a 0.4% improvement in welfare.

These findings highlight the potential problem of procyclicality that is associated with risk based capital requirements, and in particular with the IRB approach. This underlines that policy-makers must proactively apply a macroprudential overlay to capital requirements. Within current Basel rules, the Countercyclical Capital Buffer provides a tool that can be discretionarily applied for this purpose.

Our macroprudential approach to setting sectoral risk-weights provides an alternative to the Countercyclical Capital Buffer for adjusting capital requirements to the state of the financial cycle. The resultant macroprudential risk-weights that are applied adjust automatically to the sectoral financial cycle - thereby providing a more precise tool that reacts against sector-specific bubbles and credit booms. Historically, financial crises tend to arise as a result of credit booms and bubbles that are focused on particular sectors. The sectoral risk-weights that we put forward in this analysis could helpfully focus macroprudential controls over capital requirements on those sectors that are experiencing booms, whilst avoiding unwarranted impacts on other non-bubble sectors. This would potentially concentrate the impact of the tool where it needs to be to stabilise capital flows and reduce unintended spillover costs to other non-bubbly sectors.

Future research in this area could usefully assess empirically how potent risk-weight adjustments are in driving changes in bank lending behaviour. Various countries have recently imposed macroprudential interventions that have increased the risk-weights on particular assets - most often focussing on in particular these have focussed on mortgage lending. Assessing the

responsiveness of bank lending to these macroprudential policies would contribute to policy makers' and researchers' ability to evaluate the merit of using risk-weights as a tool to stabilise the economy on an ongoing basis.

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6. Appendix A: Data and Sources

6.1. Data Description

The data covers the time period January 2000 and December 2014. The dataset includes twelve variables for the Euro Area at quarterly frequency. Variables involving a trend component are made stationary using the HP filter. We follow [Hodrick and Prescott \(1997\)](#) and set the smoothing parameter for quarterly data to 1600. These variables include consumption, investment, house prices, wages, borrowing of households and firms, and deposits. The data series are transformed to log deviations from their HP-filtered trend. Finally, data on the interest rates and the inflation rate are demeaned. The time-series of the data is shown in Figure (12).

- **Consumption:** Household and NPISH final consumption expenditure, chain linked volumes (2010), seasonally adjusted and adjusted data by working days. Transformation: log deviation from HP-filtered mean. Source: Eurostat.
- **Investment:** Gross fixed capital formation, chain linked volumes (2010), seasonally adjusted and adjusted data by working days. Transformation: log deviation from HP-filtered mean. Source: Eurostat.
- **House prices:** Residential Property Valuation, new and existing dwellings, neither seasonally nor working day adjusted. Transformation: deflated by HICP inflation, log deviation from HP-filtered mean. Source: ECB.
- **Wages:** Labour cost index, whole economy excluding agriculture, fishing and government sectors, working day and seasonally adjusted. Transformation: deflated by HICP inflation, log deviation from HP-filtered mean. Source: Eurostat.
- **Inflation:** Harmonised Index of Consumer Prices (HICP), seasonally adjusted, not working day adjusted. Transformation: deviation from mean. Source: ECB.
- **Policy Rate:** Euribor 3-month - historical close, average of observations through period. Transformation: in gross quarterly form, deviation from mean. Source: ECB.
- **Borrowing rate - households:** Annualised agreed rate (AAR) / Narrowly defined effective rate (NDER), Credit and other institutions (MFI except MMFs and central banks), Lending for house purchase excluding revolving loans and overdrafts, convenience and extended credit card debt, Up to 1 year initial rate fixation, New business coverage, Households and NPISH. Transformation: in gross quarterly form, deviation from mean. Source: ECB.
- **Borrowing rate - firms:** 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, Up to 1 year initial rate fixation, Up to and including EUR 1 million amount, New business coverage, Non-Financial corporations. Transformation: in gross quarterly form, deviation from mean. Source: ECB.
- **Borrowing volume - households:** Lending for house purchase, households and NPISH, outstanding amounts at the end of the period (stocks), neither seasonally nor working day adjusted. Transformation: deflated by HICP inflation, log deviation from HP-filtered mean. Source: ECB.
- **Borrowing volume - firms:** Loans to non-financial corporations, outstanding amounts at the end of the period (stocks), neither seasonally nor working day adjusted. Transformation: deflated by HICP inflation, log deviation from HP-filtered mean. Source: ECB.

- **Deposits:** Outstanding amounts at the end of the period (stocks), MFIs excluding ESCB reporting sector - Deposits with agreed maturity, Over 1 and up to 2 years maturity, All currencies combined - Euro area (changing composition) counterpart, Households and NPISH, denominated in Euro, neither seasonally nor working day adjusted. Transformation: deflated by HICP inflation, log deviation from HP-filtered mean. Source: ECB.

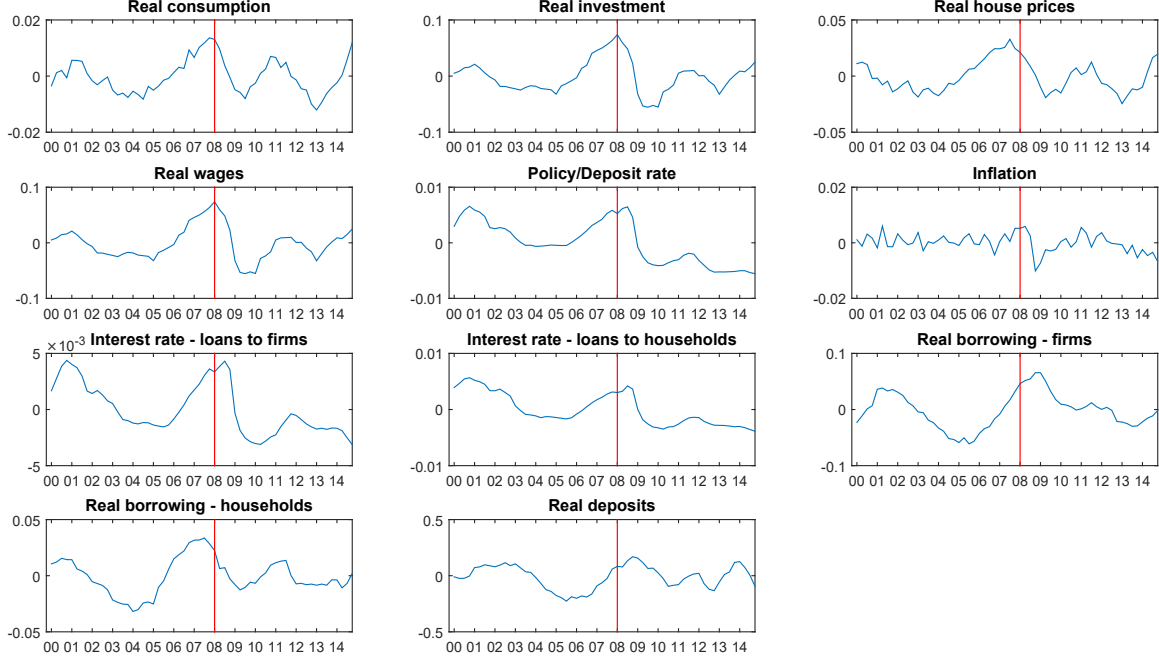


Figure 12: Transformed Data Series

7. Appendix B: Derivation of the Model's Equations

7.1. Spread expression

Given the spread equation (2.12) we have that the denominator is the following function of the ex-ante threshold $\bar{\omega}^{j,a}$:

$$X(\bar{\omega}^{j,a}) = \frac{(1 - \mu)G(\bar{\omega}_t^{j,a}, \sigma_{\bar{\omega}}^j)}{\bar{\omega}_t^{j,a}} + (1 - F(\bar{\omega}_t^{j,a}, \sigma_{\bar{\omega}}^j)) \quad (7.1)$$

or expressed with integrals:

$$X(\bar{\omega}^{j,a}) = \frac{(1 - \mu) \int_0^{\bar{\omega}_t^{j,a}} \omega f(\omega) d\omega}{\bar{\omega}_t^{j,a}} + 1 - F(\bar{\omega}^{j,a}) \quad (7.2)$$

where $f(\omega)$ is the PDF and $F(\omega)$ is the CDF of the log-normal distribution. In fact, the second term in the RHS which is the probability of non-default, expressed as 1 - the probability of default, where the latter is just the CDF evaluated at $\bar{\omega}^{j,a}$. Then it is straightforward to see that as the CDF is increasing function in $\bar{\omega}^{j,a}$ then:

$$\frac{d(1 - F(\bar{\omega}^{j,a}))}{d\bar{\omega}^{j,a}} < 0 \quad (7.3)$$

is a decreasing function in $\bar{\omega}^{j,a}$. Then calculating the derivative of the of $X(\bar{\omega}^{j,a})$ wrt $\bar{\omega}^{j,a}$ we obtain:

$$\frac{dX(\bar{\omega}^{j,a})}{d\bar{\omega}^{j,a}} = \frac{(1 - \mu)}{\bar{\omega}^{j,a}} \bar{\omega}^{j,a} f(\bar{\omega}^{j,a}) - f(\bar{\omega}^{j,a}) - \frac{(1 - \mu) \int_0^{\bar{\omega}^{j,a}} \omega f(\omega) d\omega}{(\bar{\omega}^{j,a})^2} + \frac{d(1 - F(\bar{\omega}^{j,a}))}{d\bar{\omega}^{j,a}} \quad (7.4)$$

which simplifies to:

$$\frac{dX(\bar{\omega}^{j,a})}{d\bar{\omega}^{j,a}} = -\mu f(\bar{\omega}^{j,a}) - \frac{(1-\mu) \int_0^{\bar{\omega}^{j,a}} \omega f(\omega) d\omega}{(\bar{\omega}^{j,a})^2} + \frac{d(1-F(\bar{\omega}^{j,a}))}{d\bar{\omega}^{j,a}} \quad (7.5)$$

which is negative, meaning that $X(\bar{\omega}^{j,a})$ is decreasing function of the ex-ante threshold $\bar{\omega}^{j,a}$. Then as we have from equation (10) the spread is:

$$\frac{r_t^j}{R_t^b} = \frac{1}{\frac{(1-\mu)G(\bar{\omega}_t^{j,a}, \sigma_\omega^j)}{\bar{\omega}_t^{j,a}} + (1-F(\bar{\omega}_t^{j,a}, \sigma_\omega^j))} = \frac{1}{X(\bar{\omega}^{j,a})} \quad (7.6)$$

meaning that the spread is an increasing function of the ex-ante threshold such that:

$$\frac{r_t^j}{R_t^b} = f(\bar{\omega}^{j,a}), f'() > 0 \quad (7.7)$$

which is equation (11).

7.2. Profits expression

Starting from the equation (15) of profits, dividing by the borrowing quantity b_{t-1}^j and substituting the ex-post threshold (14), we obtain profits per unit of loans as:

$$\frac{\Pi_t^j}{b_{t-1}^j} = (1-\mu)G(\bar{\omega}_t^{j,p}, \sigma_{\omega^j}^j) \frac{r_{t-1}^j}{\bar{\omega}_t^{j,p}} + (1-F(\bar{\omega}_t^{j,p}, \sigma_{\omega^j}^j))r_{t-1}^j - R_{t-1}^b \quad (7.8)$$

then from evaluating the participation constraint (7) in period $t-1$ and substituting the ex-ante threshold (6) in period $t-1$, $\bar{\omega}_{t-1}^{j,a}$ in it we have that:

$$R_{t-1}^b = (1-\mu)G(\bar{\omega}_{t-1}^{j,a}, \sigma_\omega^j) \frac{r_{t-1}^j}{\bar{\omega}_{t-1}^{j,a}} + (1-F(\bar{\omega}_{t-1}^{j,a}, \sigma_\omega^j))r_{t-1}^j \quad (7.9)$$

which can be substituted in (24) leading to:

$$\frac{\Pi_t^j}{b_{t-1}^j} = r_{t-1}^j \left[\frac{(1-\mu)G(\bar{\omega}_t^{j,p}, \sigma_{\omega^j}^j)}{\bar{\omega}_t^{j,p}} + (1-F(\bar{\omega}_t^{j,p}, \sigma_{\omega^j}^j)) - \left(\frac{(1-\mu)G(\bar{\omega}_{t-1}^{j,a}, \sigma_\omega^j)}{\bar{\omega}_{t-1}^{j,a}} + (1-F(\bar{\omega}_{t-1}^{j,a}, \sigma_\omega^j)) \right) \right] \quad (7.10)$$

Then using the formulation of $X(\bar{\omega}^{j,a})$ in (17), the last equation becomes:

$$\Pi_t^j = b_{t-1}^j r_{t-1}^j \left[- \left(X(\bar{\omega}_t^{j,a}) - X(\bar{\omega}_{t-1}^{j,p}) \right) \right] \quad (7.11)$$

And since we have showed in 5.1 that $X(\bar{\omega}^{j,a})$ is a decreasing function in $\bar{\omega}^{j,a}$, then for any $\bar{\omega}_{t-1}^{j,a} = \bar{\omega}_t^{j,p}$ the above expression would be zero, and for any $\bar{\omega}_{t-1}^{j,a} > \bar{\omega}_t^{j,p}$ we would have that $X(\bar{\omega}_t^{j,p}) > X(\bar{\omega}_{t-1}^{j,a})$ and that $\Pi_t^j > 0$ leading to:

$$\Pi_t^j = f(\bar{\omega}_{t-1}^{j,a} - \bar{\omega}_t^{j,p}), f'() > 0 \quad (7.12)$$

which is equation (16).

7.3. First order conditions of the Model

Patient households (Savers)

PHHs choose: C_t^P , H_t^P , and L_t^P to maximize:

$$E_0 \sum_{t=0}^{\infty} (\beta^P)^t U_t = E_0 \sum_{t=0}^{\infty} (\beta^P)^t \left[(1 - \alpha^P) \varepsilon_t^c \log(C_t^P(j) - \alpha^P C_{t-1}^P) + \varepsilon_t^h \log(H_t^P(j)) - \frac{(L_t^P(j))^{1+\phi}}{1+\phi} \right] \quad (7.13)$$

subject to:

$$C_t^P(j) + q_t^h \Delta H_t^P(j) + D_t(j) = W_t L_t^P(j) + \frac{R_{t-1} D_{t-1}(j)}{\pi_t} + T_t(j) \quad (7.14)$$

If we denote marginal utility of consumption with:

$$U_{C_t^P} = \Lambda_t^P = \frac{(1 - \alpha^P) \varepsilon_t^c}{C_t^P - \alpha^P C_{t-1}^P} \quad (7.15)$$

then substituting eq(31) for C_t and C_{t+1} into eq(30) and differentiating wrt. D_t we obtain the following Euler equation:

$$\Lambda_t^P = \beta^P \Lambda_{t+1}^P \frac{R_t}{\pi_{t+1}} \quad (7.16)$$

Then differentiating the infinite sum of discounted utility wrt. H_t^P gives the demand for housing:

$$\Lambda_t^P q_t^h = \frac{\varepsilon_t^h}{H_t^P} + \beta^P \Lambda_{t+1}^P q_{t+1}^h \quad (7.17)$$

Finally differentiating wrt. leisure L_t^P , we obtain the labour supply:

$$\Lambda_t^P = \frac{(L_t^P)^\phi}{W_t^P} \quad (7.18)$$

Impatient households (Borrowers)

IHHs choose: C_t^I , H_t^I , and L_t^I to maximize:

$$E_0 \sum_{t=0}^{\infty} (\beta^I)^t U_t = E_0 \sum_{t=0}^{\infty} (\beta^I)^t \left[(1 - \alpha^I) \varepsilon_t^c \log(C_t^I(i) - \alpha^I C_{t-1}^I) + \varepsilon_t^h \log(H_t^I(i)) - \frac{(L_t^I(i))^{1+\phi}}{1+\phi} \right] \quad (7.19)$$

subject to the budget constraint:

$$C_t^I + q_t^h \Delta H_t^I + \frac{(1 - F_t^p) r_{t-1}^I B_{t-1}^I}{\pi_t} + q_t^h H_{t-1}^I G_t^p = B_t^I + W_t L_t^I \quad (7.20)$$

and ex-post default threshold:

$$\bar{\omega}_t^{p,I} = \frac{r_{t-1}^I B_{t-1}^I}{q_t^h H_{t-1}^I \pi_t} \quad (7.21)$$

If we denote marginal utility of consumption with:

$$U_{C_t^I} = \Lambda_t^I = \frac{(1 - \alpha^I) \varepsilon_t^c}{C_t^I - \alpha^I C_{t-1}^I} \quad (7.22)$$

By taking differentiating lifetime utility wrt. B_t^I we obtain the following Euler equation:

$$\Lambda_t^I = \beta^I \Lambda_{t+1}^I \frac{r_t^I}{\pi_{t+1}} \quad (7.23)$$

Differentiating wrt H_t gives the following housing demand:

$$\Lambda_t^I q_t^h = \beta^I \Lambda_{t+1}^I q_{t+1}^h + \frac{\varepsilon_t^h}{H_t^I} \quad (7.24)$$

Lastly, labour supply:

$$\Lambda_t^I = \frac{(L_t^I)^\phi}{W_t^I} \quad (7.25)$$

Entrepreneurs

Choose consumption C_t^E , physical capital K_t^E , loans from banks B_t^E , degree of capital utilization, and labour inputs from patient and impatient households L_t^P, L_t^I to maximize:

$$E_0 \sum_{t=0}^{\infty} \beta_t^I \left[(1 - \alpha^E) \log(C_t^E(i) - \alpha^E C_{t-1}^E) \right] \quad (7.26)$$

subject to:

$$\begin{aligned} C_t^E + W_t^P L_t^P + W_t^I L_t^I + \frac{(1 - F_t^{p,E}) r_{t-1}^E B_{t-1}^E(i)}{\pi_t} + q_t^k [K_t^E - (1 - \delta) K_{t-1}^E] + \\ q_t^k K_{t-1}^E G_t^{p,E} = \frac{Y_t^E}{X_t} + B_t^E \end{aligned} \quad (7.27)$$

with production function:

$$Y_t^E(i) = A_t^E K_{t-1}^E(i)^\alpha L_t^E(i)^{1-\alpha} \quad (7.28)$$

where: $L_t^E = (L_t^P)^\nu (L_t^I)^{1-\nu}$

subject to an ex-post default threshold:

$$\bar{\omega}_t^{p,E} = \frac{r_{t-1}^E B_{t-1}^E}{q_t^k K_{t-1}^E} \quad (7.29)$$

Denoting marginal utility of consumption as:

$$\Lambda_t^E = \frac{(1 - \alpha^e)}{C_t^E - \alpha^e C_{t-1}^E} \quad (7.30)$$

Differentiating lifetime utility wrt. K_t^E leads to:

$$\Lambda_t^E q_t^k = \Lambda_{t+1}^E \beta^E \left(q_{t+1}^k (1 - \delta) + r_{t+1}^k \right) \quad (7.31)$$

where r_t^k is the rental rate of capital: $r_t^k = \frac{\alpha Y_t^E}{K_{t-1}^E} \frac{1}{X_t}$

For labour demand we have MP of each labour type equal to its MC:

$$W_t^P = \frac{\nu(1 - \alpha) Y_t^E}{L_t^P X_t} \quad W_t^I = \frac{(1 - \nu)(1 - \alpha) Y_t^E}{L_t^I X_t} \quad (7.32)$$

Finally the Euler equation is:

$$\Lambda_t^E = \frac{\Lambda_{t+1}^E \beta^E r_t^E}{\pi_{t+1}} \quad (7.33)$$

Capital Producers

Using the discount factor of entrepreneurs (as being owned by them), capital producers maximize:

$$E_0 \sum_{t=0}^{\infty} \Lambda_t^E (\beta^E)^t \left[q_t^k \Delta x_t - I_t \right] \quad (7.34)$$

by choosing Δx_t and I_t subject to the following constraint:

$$\Delta x_t = \left[1 - \frac{\kappa_i}{2} \left(\frac{I_t \varepsilon_t^k}{I_{t-1}} - 1 \right)^2 \right] I_t \quad (7.35)$$

Where, $\Delta x_t = K_t - (1 - \delta)K_{t-1}$. Differentiating wrt. I_t we obtain:

$$\Lambda_t^E \left[q_t^k \frac{\partial \Delta x_t}{\partial I_t} - 1 \right] + \Lambda_{t+1}^E \beta^E \left[q_{t+1}^k \frac{\partial \Delta x_{t+1}}{\partial I_t} \right] = 0 \quad (7.36)$$

for the partial derivatives we obtain:

$$\frac{\partial \Delta x_t}{\partial I_t} = 1 - \frac{\kappa_i}{2} \left(\frac{I_t \varepsilon_t^k}{I_{t-1}} - 1 \right)^2 - \kappa_i \left(\frac{I_t \varepsilon_t^k}{I_{t-1}} - 1 \right) \frac{I_t \varepsilon_t^k}{I_{t-1}} \quad (7.37)$$

$$\frac{\partial \Delta x_{t+1}}{\partial I_t} = \kappa_i \left(\frac{I_{t+1} \varepsilon_{t+1}^k}{I_t} - 1 \right) \left(\frac{I_{t+1}}{I_t} \right)^2 \varepsilon_{t+1}^k \quad (7.38)$$

substituting the last two into 52 we obtain the optimality condition:

$$1 = q_t^k \left[1 - \frac{\kappa_i}{2} \left(\frac{I_t \varepsilon_t^k}{I_{t-1}} - 1 \right)^2 - \kappa_i \left(\frac{I_t \varepsilon_t^k}{I_{t-1}} - 1 \right) \frac{I_t \varepsilon_t^k}{I_{t-1}} \right] + \beta^E E_t \left[\frac{\Lambda_{t+1}^E q_{t+1}^k \varepsilon_{t+1}^k}{\Lambda_t^E} \kappa_i \left(\frac{I_{t+1} \varepsilon_{t+1}^k}{I_t} - 1 \right) \left(\frac{I_{t+1}}{I_t} \right)^2 \right]$$

Retailers

Thus retailers choose $P_t(j)$ to maximize:

$$E_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^P \left[P_t(j) Y_t(j) - P_t^W Y_t(j) - \frac{\kappa_p}{2} \left(\frac{P_t(j)}{P_{t-1}(j)} - \pi_{t-1}^{i_p} \pi^{1-i_p} \right)^2 P_t Y_t \right] \quad (7.39)$$

subject to: $Y_t(j) = \left(\frac{P_t(j)}{P_t} \right)^{-\epsilon_t^y} Y_t$.

Thus the part of the infinite sum that includes $P_t(j)$ is:

$$\begin{aligned} \sum^R &= \Lambda_t^P \left[Y_t(j) (P_t(j) - P_t^W) - \frac{\kappa_p}{2} \left(\frac{P_t(j)}{P_{t-1}(j)} - \pi_{t-1}^{i_p} \pi^{1-i_p} \right)^2 P_t Y_t \right] + \\ &\Lambda_{t+1}^P \beta^P \left[Y_{t+1}(j) (P_{t+1}(j) - P_{t+1}^W) - \frac{\kappa_p}{2} \left(\frac{P_{t+1}(j)}{P_t(j)} - \pi_t^{i_p} \pi^{1-i_p} \right)^2 P_{t+1} Y_{t+1} \right] \end{aligned} \quad (7.40)$$

Differentiating wrt. $P_t(j)$ and imposing $P_t(j) = P_t$ leads to:

$$\begin{aligned} \Lambda_t^P \left[-\epsilon_t^y Y_t + \frac{\epsilon_t^y Y_t}{X_t} + Y_t - \kappa_p (\pi_t - \pi_{t-1}^{i_p} \pi^{1-i_p}) P_t Y_t \frac{1}{P_{t-1}(j)} \right] + \\ \Lambda_{t+1}^P \beta^P \left[\kappa_p (\pi_{t+1} - \pi_t^{i_p} \pi^{1-i_p}) P_{t+1} Y_{t+1} \frac{P_{t+1}(j)}{P_t^2(j)} \right] = 0 \end{aligned} \quad (7.41)$$

which after dividing by Y_t and Λ_t^P simplifies to:

$$1 - \epsilon_t^y + \frac{\epsilon_t^y}{X_t} - \kappa_p (\pi_t - \pi_{t-1}^{i_p} \pi^{1-i_p}) \pi_t + \frac{\Lambda_{t+1}^P \beta^P}{\Lambda_t^P} \kappa_p (\pi_{t+1} - \pi_t^{i_p} \pi^{1-i_p}) \frac{Y_{t+1}}{Y_t} \pi_{t+1}^2 = 0 \quad (7.42)$$

where we use that $1/X = P_t^W/P_t$ and $\pi_t = P_t/P_{t-1}$

The profits of retailers that are transferred back to savers are given by

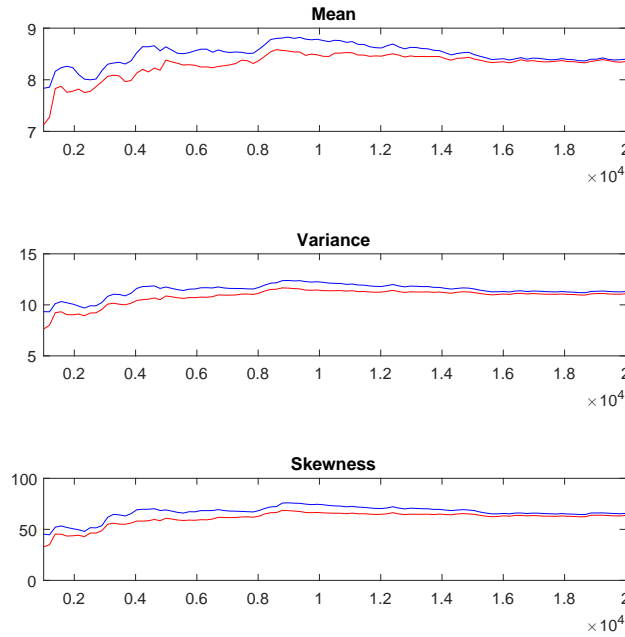
$$J_t^R = Y_t \left(1 - \frac{1}{X_t} \right) - \kappa_p (\pi_t - \pi_{t-1}^{i_p} \pi^{1-i_p})^2 \quad (7.43)$$

8. Appendix C: Robustness and Additional Results

8.1. Estimation Convergence

Below, we plot the multivariate convergence statistics for mean, variance and skewness following [Brooks and Gelman \(1998\)](#). For each statistic, the red line represents the within-sequence values while the blue represents the sum of the within-sequence and a between-sequence variance. As a result, the convergence of the two lines represents the convergence of the estimated parameters. Figure (13) shows that the statistics of the Metropolis-Hastings algorithm converge over the employed 200,000 replications.³⁹

Figure 13: Estimation - Multivariate Convergence Diagnostics



For an additional robustness check, we ran an additional estimation using a single chain with 500,000 replications, in order to see if the summary statistics of the posterior distribution change. Overall, the summary statistics for the posterior distribution did not change (compared to the one reported in section 3.3). In what follows, we limit ourselves to report the minor changes that we have found. The results show minuscule differences in the posterior modes of less than 1% deviation for all parameters. In addition, we find very similar values for the posterior means. The only exception concerns the parameter governing the sensitivity of output in the Taylor Rule, ϕ_y , the posterior mean is around of 8% larger compared to our baseline where we used 200,000 replications.

Finally, and following [Geweke \(1992\)](#) we compute convergence diagnostics using a chi-square test to compare the means of the first and last draws in the simulation, which in our case are those in the intervals 100,000 to 180,000 versus 300,000 to 500,000. The resulting p-values are significant at the 5% level - confirming that the estimated parameters converge.

³⁹Upon request, the convergence statistics are also available on single estimated parameter levels. Due to the extensive output we do not report these results here.

8.2. Model Responses to Standard Shocks

In this section we report the behaviour of the estimated model in terms of responses to technology and monetary shocks. In doing so we compare our results with [Gerali et al. \(2010\)](#) as a closely related model.

Figure (14) shows the impulse responses of our model to a positive technology shock, while Figure (15) shows the corresponding simulation results in [Gerali et al. \(2010\)](#). For most variables, the responses of our model are very similar to the benchmark simulations (BK) of [Gerali et al. \(2010\)](#). However, the impulse response of bank capital differs significantly from [Gerali et al. \(2010\)](#). This result is not surprising given the different model structure of the banking sector. In [Gerali et al. \(2010\)](#), the interest rate setting at the retail level is driven entirely by sticky prices, due to the absence of defaulting loans in the model. In contrast, our model allows for defaulting loans and hence banks are facing not only a proportion of non-repaid loans but are also exposed to the value of the repossessed collateral. As a result, in our setting bank profits and bank capital are driven not only by the interest rate margin but also by the proportion of defaulted loans and the value of the repossessed collateral. Therefore, a lower than expected default rate with higher than expected value of repossessed collateral leads to positive profits by banks and higher capital.⁴⁰ On the contrary, for the same shock [Gerali et al. \(2010\)](#) reports countercyclical bank capital which is counterfactual.

Figure (16) shows the impulse responses of our model to a contractionary monetary policy shock, while Figure (17) shows the corresponding simulation results in [Gerali et al. \(2010\)](#). For most variables, the responses of our model are very similar to the benchmark simulations (BK) of [Gerali et al. \(2010\)](#).

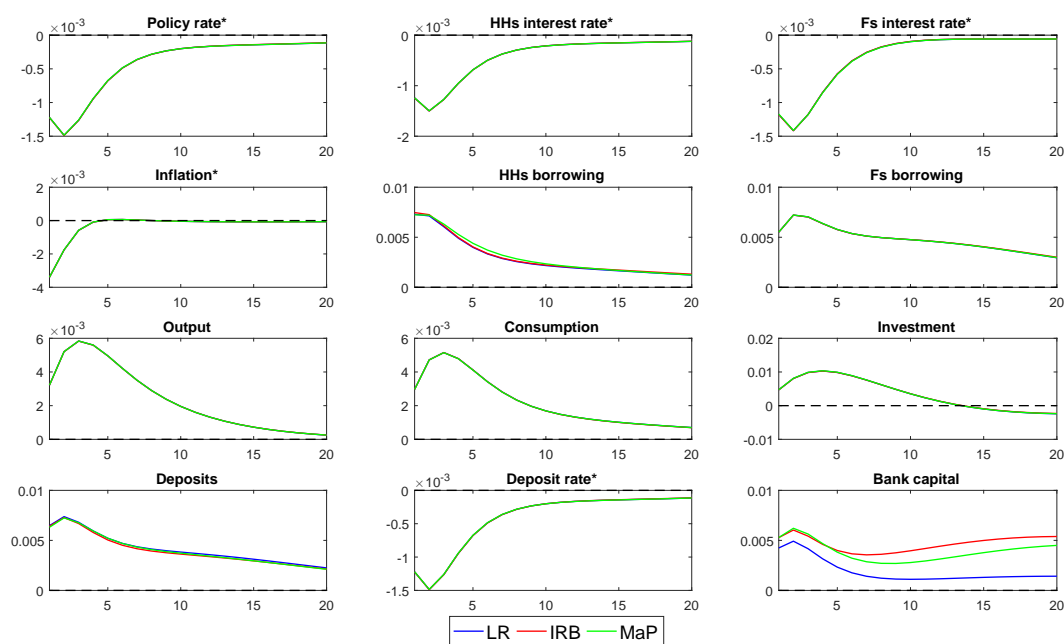


Figure 14: IRF - Positive Technology Shock (one standard deviation)

⁴⁰See section 2.3.3 for bank profits equations.

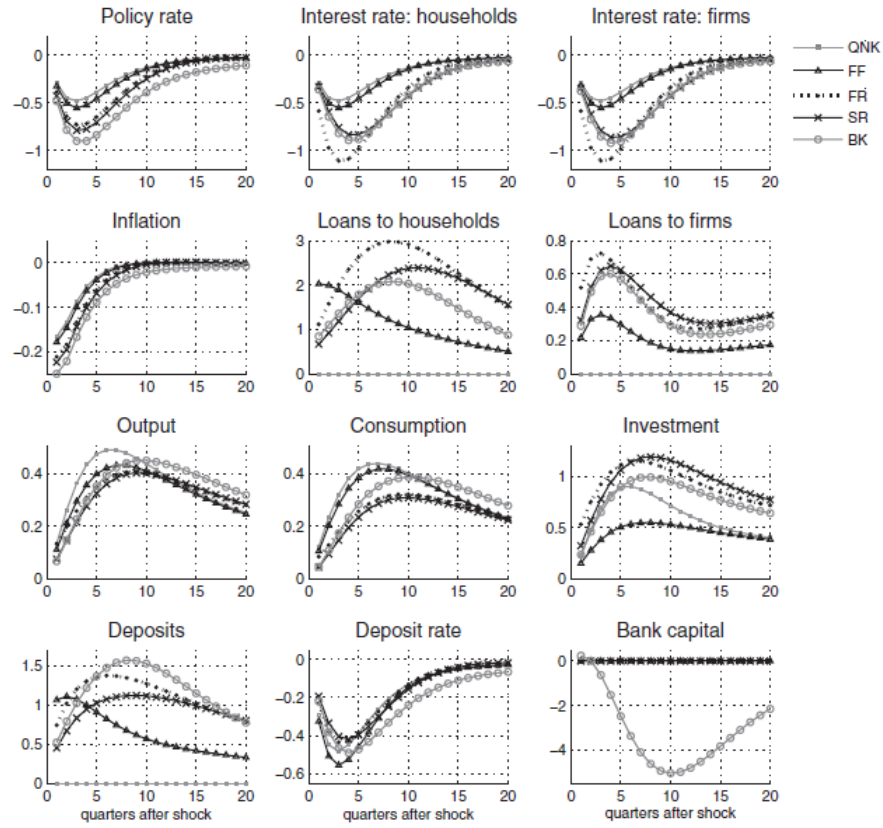


Figure 15: IRF - Positive Technology Shock - (Gerali et al., 2010)

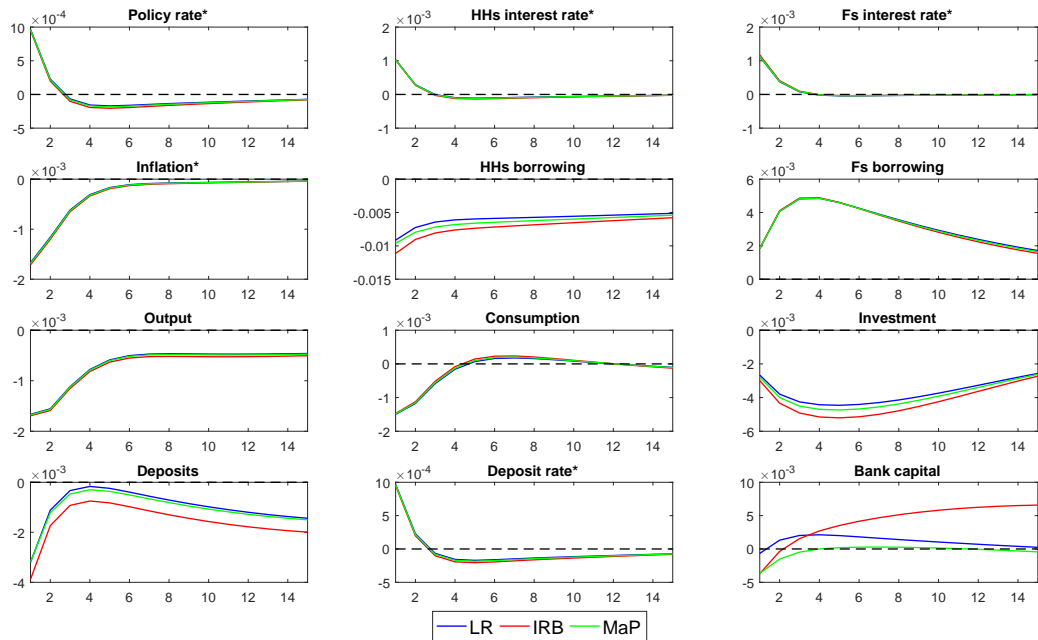


Figure 16: IRF - Monetary Policy shock

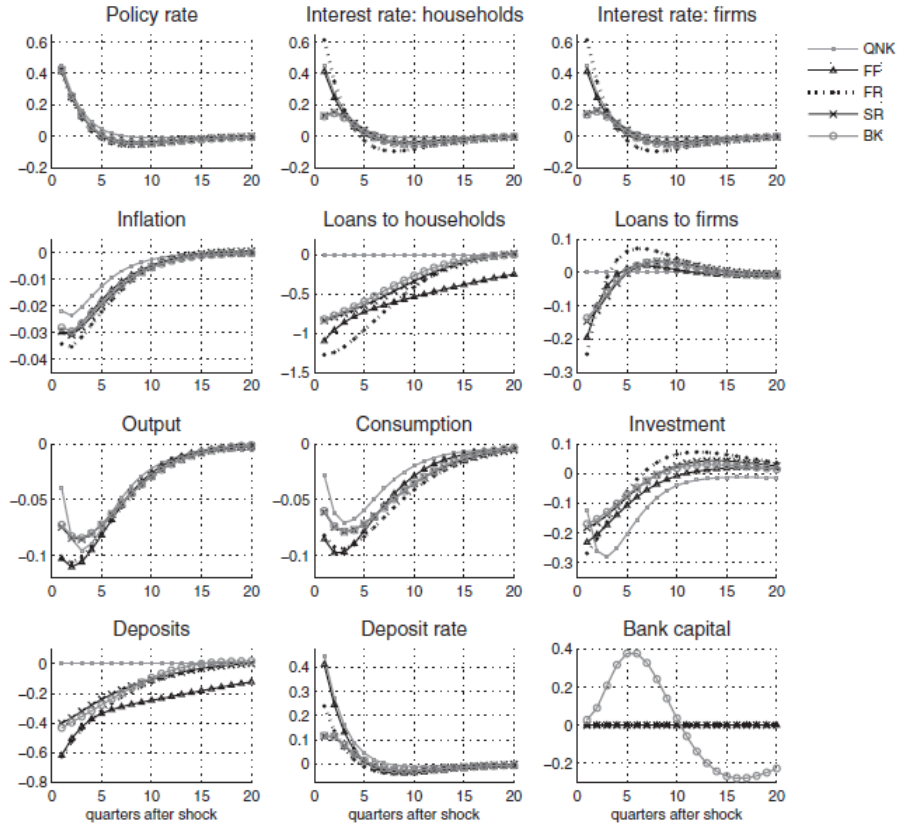


Figure 17: IRF - Monetary Policy shock - (Gerali et al., 2010)

8.3. Alternative Crisis Scenario - Shock to Firm Loans

Figure 18: IRF - unexpected shock to σ^e

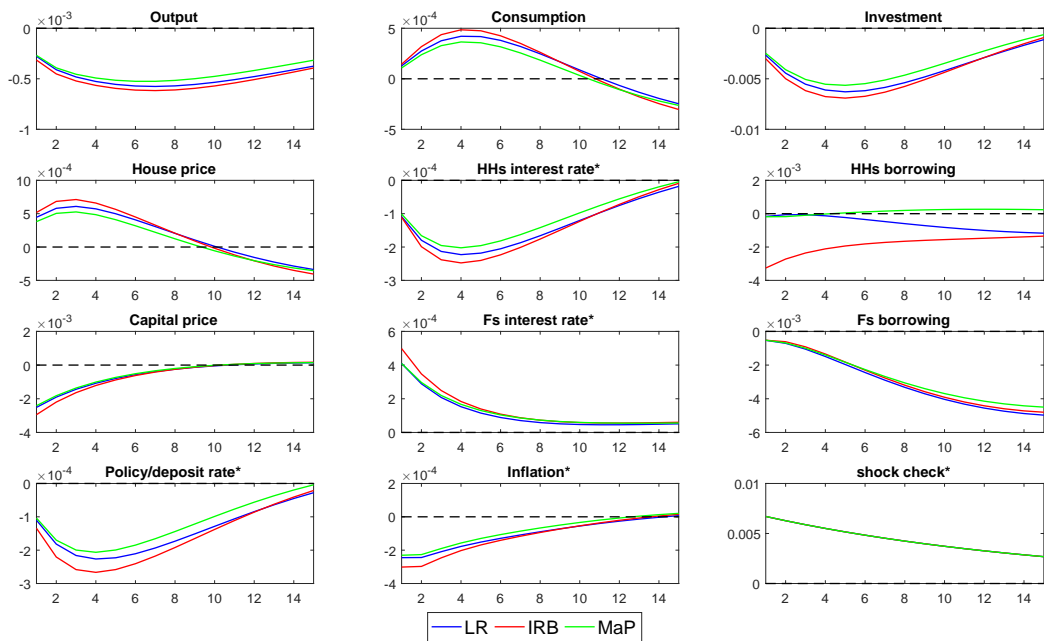
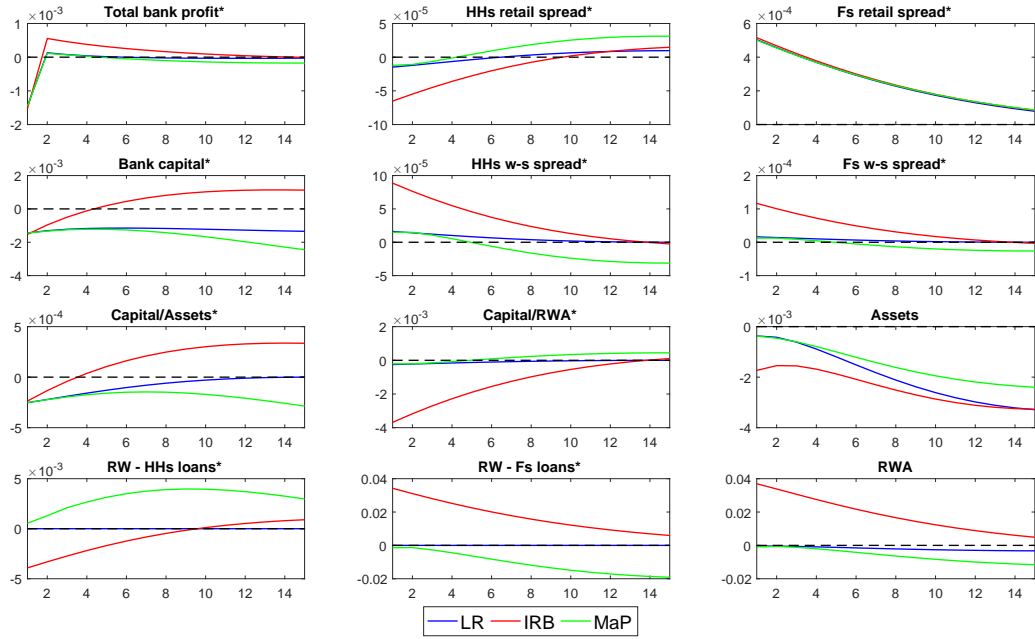


Figure 19: IRF - unexpected shock to σ^e



8.4. Alternative Crisis Scenario - Exogenous Destruction of Bank Capital

Figure 20: IRF - unexpected shock to K^b

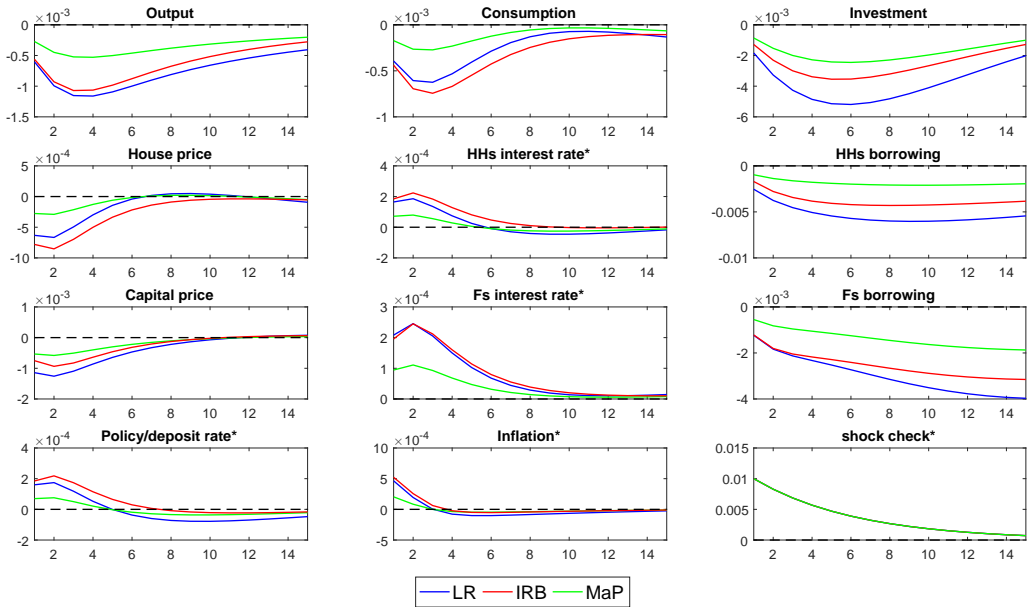
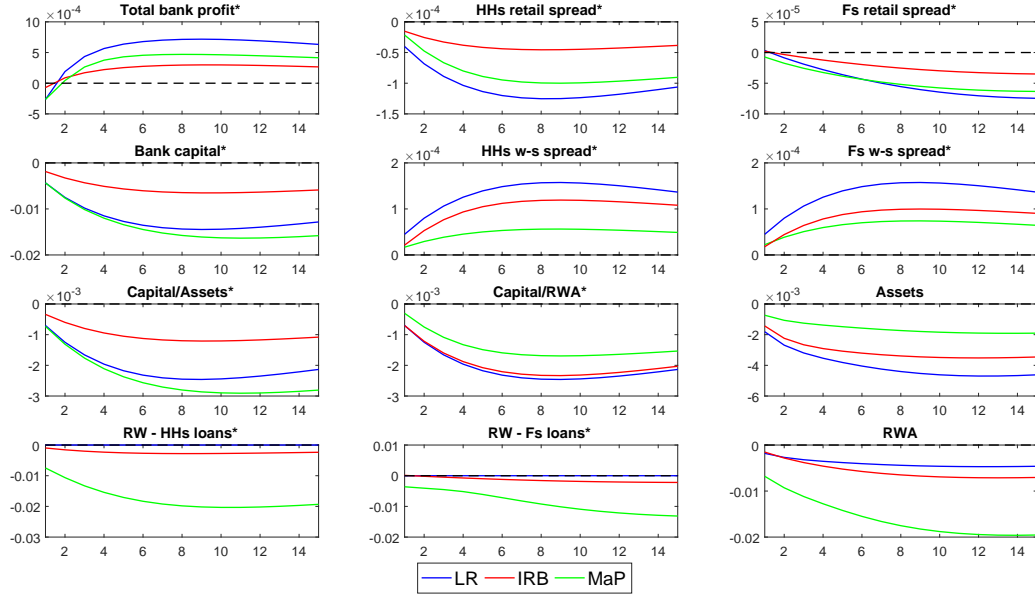


Figure 21: IRF - unexpected shock to K^b



8.5. Optimal Macprudential Rule

Figure 22: IRF - unexpected shock to σ^i

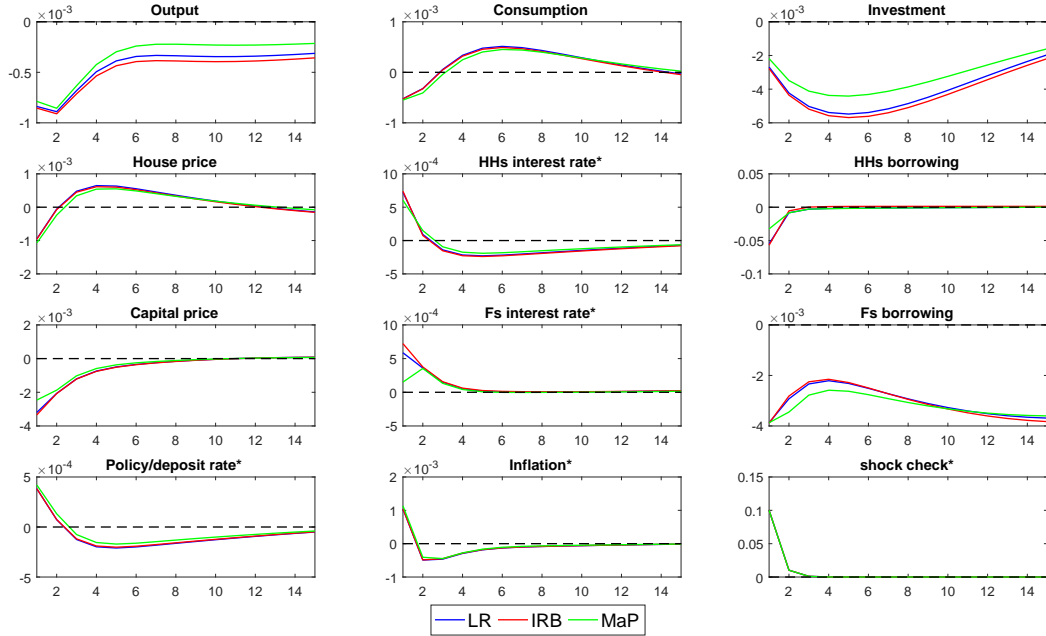


Figure 23: IRF - unexpected shock to σ^i

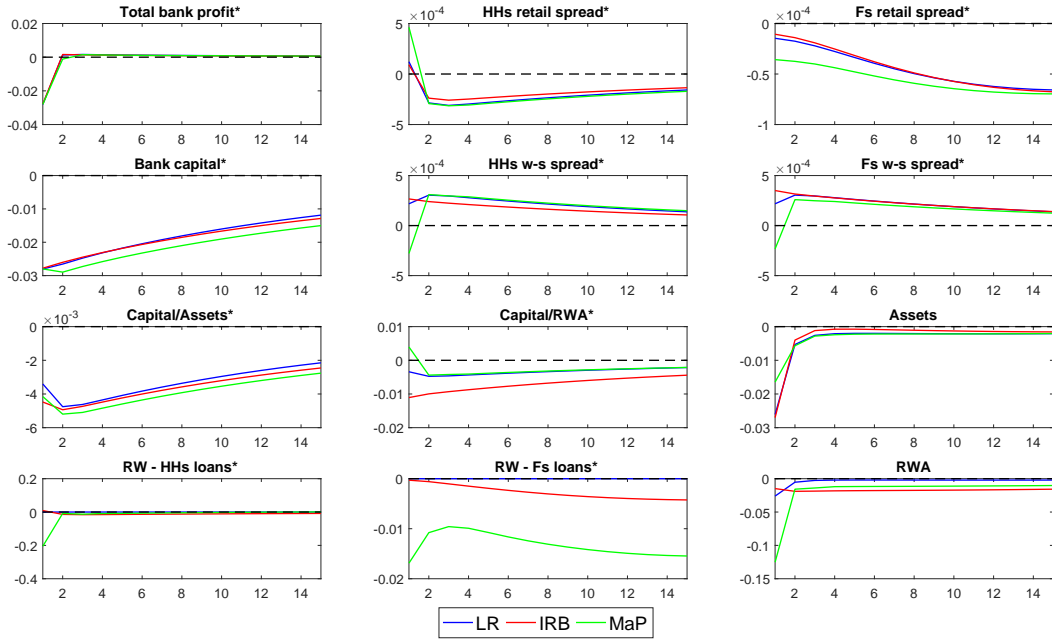


Figure 24: IRF - unrealized news shock to σ^i at period 4

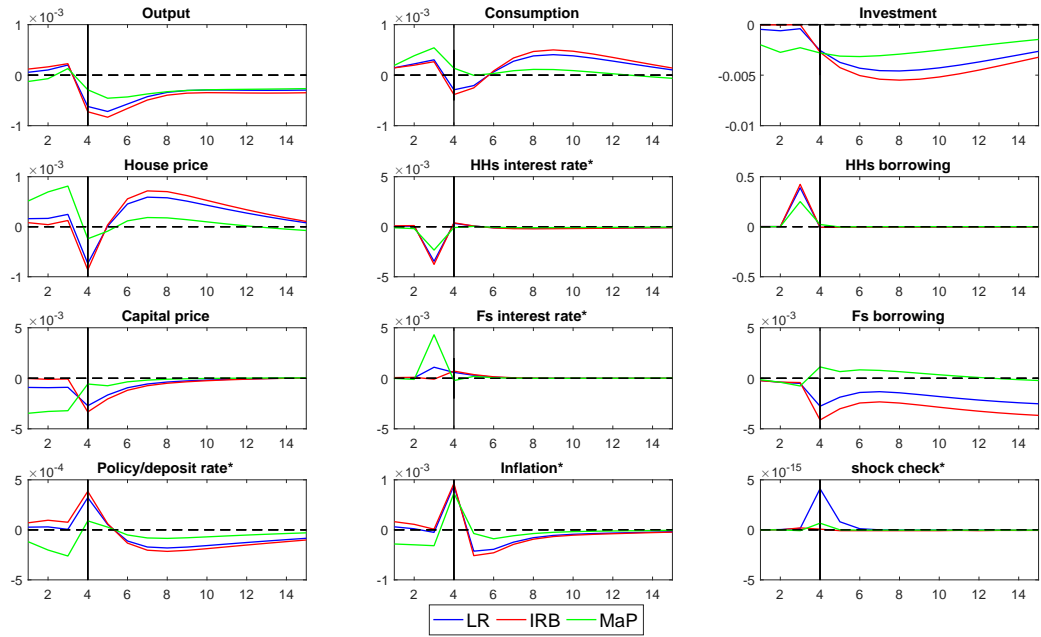


Figure 25: IRF - unrealized news shock to σ^i at period 4

