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Jonathan Acosta-Smith,[(1)] Marzio Bassanin[(2)] and Ivy Sabuga[(3)]

Abstract

We assess the macroeconomic effects of the output floor, a new regulatory constraint introduced as part of the Basel III framework. The output floor is designed to provide a backstop against excessively low risk-weighted assets (RWA) modelled by banks relative to the riskiness of the underlying exposures. Our model shows that it counteracts the downward pressure on modelled RWA during economic expansions and, in turn, reduces the cyclicality of risk-weighted capital requirements. This mitigates increases in the credit-to-GDP ratio and supports the objectives of the macroprudential authority. Our analysis also uncovers important sectoral effects. Estimating the model for the UK economy, we find that during an expansion the output floor dampens the growth of mortgage lending but amplifies the expansion of lending to firms, although the latter effect is more than offset by the former.

Key words: Capital regulation, output floor, macroprudential policy, DSGE models.

JEL classification: E32, E44, E58.

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(1) The Organisation of Economic Co-Operation and Development. Email: Jonathan.SMITH@oecd.org
(2) Bank of England. Email: Marzio.Bassanin@bankofengland.co.uk
(3) International Monetary Fund. Email: ISabuga@imf.org

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Bank of England, Threadneedle Street, London, EC2R 8AH
Email: enquiries@bankofengland.co.uk

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1 Introduction

The Basel III capital framework is built on the principle that banks' capital requirements should reflect the risks on their balance sheets. To achieve this, banks assign risk weights to different types of assets, so that riskier assets attract higher capital charges. Under Basel III, and subject to approval from the relevant supervisory authority, banks may use their own internal models to estimate these risk weights. This approach offers clear advantages: it links capital more closely to actual risk and allows banks - who are closest to the underlying exposures - to draw on detailed information to estimate risk more accurately.

However, the Global Financial Crisis (GFC) exposed important weaknesses in this model-based system. In practice, the risk weights generated by banks' internal models did not fully capture the true riskiness of their portfolios and were far more volatile than expected. This volatility amplified the economic cycle by making capital requirements fall too far during booms and rise too sharply during downturns (Repullo and Suarez (2016)). This, in turn, has a negative impact on lending dynamics (Behn, Haselmann and Wachtel (2016)) and systemic risk (Acharya, Engle and Pierret (2014), Hellwig (2010), and Vallascas and Hagendorff (2013)). The crisis also highlighted that similar banks could report significantly different risk weights, undermining confidence in the framework's credibility.

Recognising these shortcomings, the Basel Committee on Banking Supervision (BCBS) introduced several reforms to restore trust in risk-weighted capital requirements. An initial step was the leverage ratio - a simple, non-risk-based measure designed to provide a backstop against the under-statement of risk (BCBS (2014), Gambacorta and Karmakar (2018) and Mankart, Michaelides and Pagratis (2020)). But because it does not address concerns about the variability of risk-weighted assets (RWA) themselves, the BCBS went further.

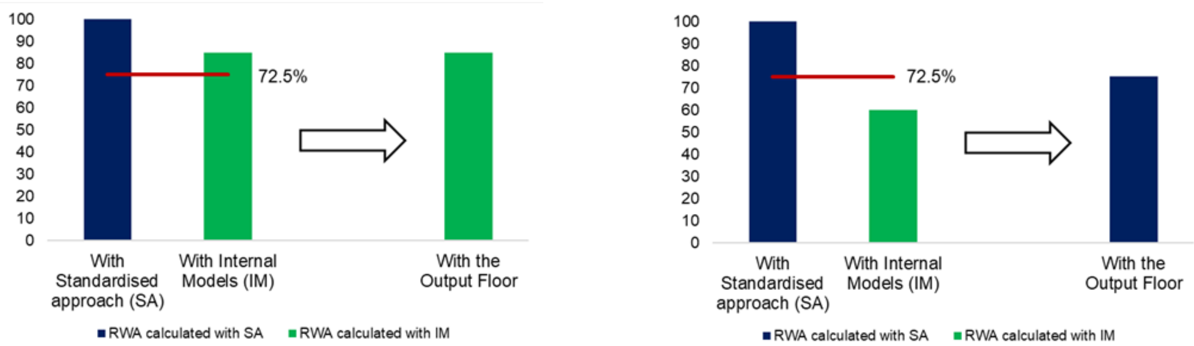
In 2017, BCBS introduced a new set of reforms known as the Basel III finalisation package (BCBS (2017)), with the aim of improving trust in how banks calculate RWA. Among these reforms is the output floor, a new requirement that limits how far a bank's internally modelled (IM) RWA can deviate from the amount calculated using the standardised approach (SA).[1] Under this rule, the RWA used to determine capital requirements must be no lower than 72.5% of the standardised RWA. In practice, when a bank's internal model generates very low risk weights, the output floor prevents RWA from falling below a minimum level set by regulators. In the UK, the output floor will take effect on January 2027 (BoE (2026)). It will be implemented

[1]The standardised approach is a rule-based method in which regulators assign fixed risk weights to exposures based on external credit ratings and asset classes. This approach is simpler than internal models, under which banks with supervisory permission may use their own statistical models and historical data to estimate risk parameters such as the Probability of Default (PD) and Loss Given Default (LGD).

over a phased period, increasing from 60% of standardised RWA to its final level of 72.5% in January 2030 (BoE (2024)).

Figure 1 describes how the output floor works. In case (a), the RWA calculated with internal models (IM) are larger than 72.5% of the RWA calculated with the SA, hence the output floor does not bind and RWA is set according to internal models. In case (b), the output floor binds because the RWA calculated with internal models is lower than 72.5% of the RWA calculated with the SA. And the bank's RWA flip to being calculated with the SA scaled down by 72.5%.

Figure 1: The output floor at work



(a) The output floor does not bind

(b) The output floor binds

The output floor is designed to reduce the wide differences seen across banks that use internal models, especially when institutions have similar risk profiles. The standardised approach assigns the same regulatory risk weights across banks and does not vary with economic conditions, whereas internal models tend to respond strongly to changes in the economic cycle. As a result, the output floor helps stabilise RWA by setting a consistent lower bound. Institutional assessments (EBA (2019*b*), EBA (2019*a*) and Santos et al. (2020) among others) suggest that the output floor will both reduce variation in RWA and help rebuild confidence in the risk-weighted framework. These studies also highlight the potential for banks to adjust their asset mix in response to the new constraint. This reflects the fact that the difference between modelled and standardised risk weights (the IM-SA gap) varies substantially across asset classes. Standardised risk weights are often higher than those produced by internal models, but the size of this gap differs across asset types. For assets where the IM-SA gap is small, the 72.5% floor places a tighter constraint and may reduce the capital cost of holding those assets relative to others. Conversely, for assets with large gaps, the output floor raises capital requirements more substantially. As a result, banks may find it more attractive - at the margin - to increase exposures to assets with relatively small IM-SA gaps if the output floor binds.

Table 1 explains this mechanism using a stylised example of a bank with two assets. The assumptions behind the example are the following:

- The bank holds £500 of a *"High IM-SA gap"* asset and £750 of *"Low IM-SA gap"* asset;
- *"High IM-SA gap"* asset has a modelled RW equal to 0.35 and a standardised RW equal to 0.65 – i.e. the modelled RW is 54% of the standardised one;
- *"Low IM-SA gap"* asset has a modelled RW equal to 0.32 and a standardised RW equal to 0.38 – i.e. the modelled RW is 84% of the standardised one; and,
- The bank is subject to a 9% (over RWA) capital requirement and the output floor binds.

The output floor results in an increase in total capital requirements (from £37.4 to £41.2). However, the effect on the two asset classes is asymmetric. The marginal contribution of the high IM-SA gap asset rises (from £15.8 to £21.9) when the output floor binds. By contrast, the contribution of the low IM-SA gap asset is £2.4 lower under the output floor because the 72.5% floor applied to standardised risk weights reduces its capital impact more than the IM-SA gap alone. In this case, all else being equal, the bank may have an incentive to expand its exposure to the low IM-SA gap asset when the output floor binds.

Table 1: Portfolio composition and the output floor[2]

Capital requirements	Contribution from *"High IM-SA gap"* asset (a)	Contribution from *"Low IM-SA gap"* asset (b)	Total (a) + (b)
Output Floor (OF)	21.2	18.6	39.8
Internal Models (IM)	15.8	21.6	37.4
Differences (OF - IM)	5.5	-3.0	2.4

Our contribution. This paper contributes to the assessment of the output floor by examining its cyclical effects - specifically, how the output floor influences macroeconomic fluctuations once it is fully implemented at its final calibration of 72.5%.[3] To do this, we develop a general

[2]Capital requirements under the Output Floor (OF) are calculated as: Total = 0.09*(0.725*(0.65*500 + 0.38*750)) = 39.8; *"High IM-SA gap"* asset contribution = 0.09*(0.725*(0.65*500)) = 21.2; *"Low IM-SA gap"* asset contribution = 0.09*(0.725*(0.38*750) = 18.6. Capital requirements under Internal Models (IM) are calculated as: Total = 0.09*(0.35*500 + 0.32*750) = 37.4; *"High IM-SA gap"* asset contribution = 0.09*(0.35*500) = 15.8; *"Low IM-SA gap"* asset contribution = 0.09*(0.32*750) = 21.6. Differences difference (OF - IM) are calculated as: Total = (41.2 - 37.4) = 3.8; *"High IM-SA gap"* asset contribution = (21.9 - 15.8) = 6.2; *"Low IM-SA gap"* asset contribution = (19.2 - 21.6) = -2.4.

[3]The paper, instead, does not consider the possible effects generated during the transition from the current regime (without the output floor) and the new regime which includes the output floor. Similarly, we do not consider the effect of the output floor during its phased period in which it will increase from 50% to 72.5%.

equilibrium model that investigates three key aspects:(i) how the output floor alters the volatility of risk-weighted assets (RWA); (ii) how it affects the cyclicality of capital requirements and lending; and (iii) how it interacts with the macroprudential authority's objectives.

To our knowledge, this is the first study to provide a structural, model-based evaluation of the extent to which the output floor mitigates long-standing concerns about internal-model cyclicality. Following the approach of Angelini, Neri and Panetta (2014), we use a dynamic stochastic general equilibrium (DSGE) framework with a two-asset banking sector, financial frictions, sticky interest rates and binding capital requirements. Our starting point is the established model of Gerali et al. (2010), which allows us to benchmark the effects of the output floor against a well-recognised macroprudential environment.

In our version of the model, the banking system can operate under two regulatory regimes: one in which banks determine RWA using internal models, and another where the output floor constrains those modelled RWA. Because the output floor introduces a non-linear "maximum" operator, we solve the model using the method developed by Holden (2016), which is designed for occasionally binding constraints. We estimate the model using UK data and then compare how the two regimes behave over the economic cycle.

Our analysis yields three main findings. First, the output floor reduces the procyclicality of capital requirements and lending. During economic expansions, modelled risk weights fall, lowering RWA and loosening capital constraints; the output floor counteracts this by preventing RWA from falling too far, which in turn moderates the rise in the credit-to-GDP ratio. This supports the use of the output floor as a macroprudential stabiliser.

Second, we examine whether the output floor encourages banks to adjust their portfolios, as suggested by policy assessments. We find that, during an expansionary phase, the output floor dampens the expansion in mortgage lending but strengthens the expansion in lending to firms. This reflects differences in the gap between modelled and standardised risk weights. Since the IM-SA gap is smaller for corporate lending, the output floor reduces its relative capital cost. A larger gap for mortgages, instead, makes them more expensive for banks. At the aggregate level, the stronger expansion in lending to firms is largely offset by the muted growth in mortgages, resulting in a modest overall effect on credit-to-GDP and real GDP. However, these sectoral shifts highlight potential distributional effects on the real economy and on banks' risk profiles.

Finally, we assess whether the output floor supports macroprudential objectives by examining the macroprudential authority's loss function. We find that the output floor materially reduces the volatility of both RWA and credit-to-GDP ratio over time, thereby strengthening the ability of the macroprudential authority to stabilise the financial cycle. Policymakers typically emphasise the output floor's role in reducing cross-sectional variation in RWA, but our results suggest it also delivers substantial benefits by reducing time-series volatility. This has implications for the design of stress tests and the calibration of prudential tools.[4]

Literature review. A wide body of research examines the limitations of model-based regulation and the potential benefits of alternative prudential tools. Hodbod, Huber and Vasilev (2018) show that adjusting sectoral risk weights countercyclically can help stabilise capital requirements, outperforming the leverage ratio in moderating credit cycles. Similarly, Gambacorta and Karmakar (2018) find that internally modelled risk weights often fail to capture banks' underlying portfolio risks, contributing to greater systemic risk. Their results suggest that complementing risk-sensitive frameworks with a simple, non-risk-based leverage ratio can provide meaningful stability benefits. Mankart, Michaelides and Pagratis (2020) estimate a dynamic structural banking model to examine the interaction between risk-weighted capital adequacy and un-weighted leverage requirements. They find that tighter leverage requirements, differently from tighter risk-weighted capital requirements, increase lending, preserve bank charter value and incentives to accumulate equity buffers, therefore leading to lower bank failure rates.

Other influential studies underline the procyclicality of the Basel framework. Angeloni and Faia (2013) demonstrate that internally modelled capital ratios can amplify economic fluctuations, strengthening the case for countercyclical capital buffers. Angelini, Neri and Panetta (2014) incorporate risk-weighted capital requirements into the DSGE model of Gerali et al. (2010) and provide formal evidence of procyclicality in the internally modelled risk weights.

Our work also relates to the substantial empirical literature documenting weaknesses in model-based regulation. Behn, Haselmann and Vig (2016), Goodhart, Hofmann and Segoviano (2014) and Kashyap and Stein (2004) all highlight the procyclical patterns and scope for gaming that arise when banks determine risk weights internally. Santos et al. (2020) show that banks understated risk weights in the run-up to the 2007-08 global financial crisis, particularly for assets that later experienced severe losses. These findings collectively provide strong empirical support for our assumption that modelled risk weights respond excessively to economic conditions.

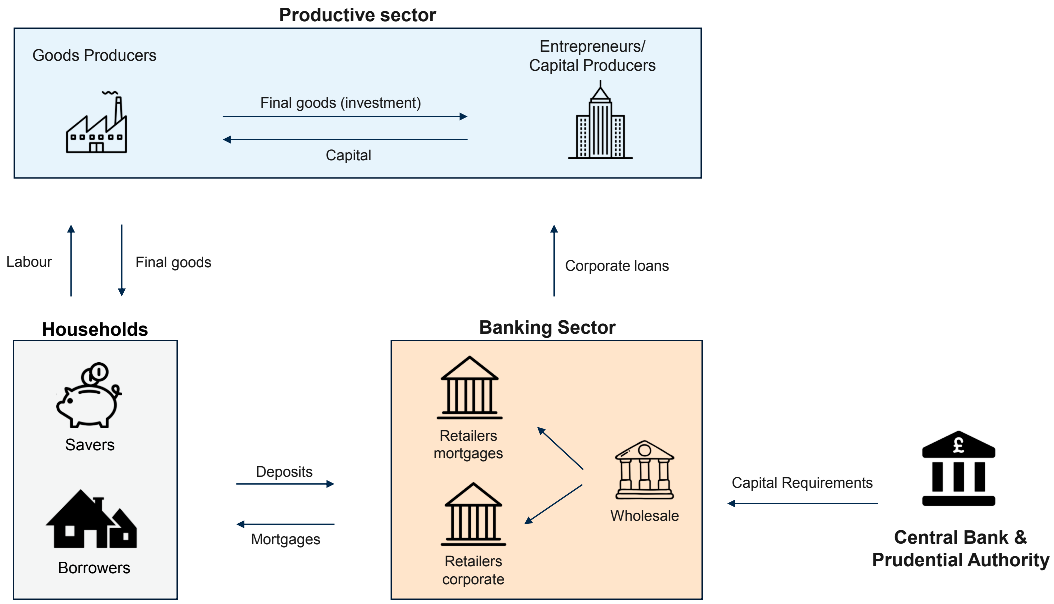
Structure of the paper. The paper is structured as follows. Section 2 describes the model and Section 3 its estimation. Section 4 presents the model analysis. Section 5 concludes.

[4]Although there are important interactions between the output floor and the leverage ratio, as both act as backstops to shortcomings in risk-based regulation, this paper focuses only on the former. We prioritise evaluating the output floor in isolation to avoid the additional complexity arising from its interaction with other instruments. The interaction between the output floor and the leverage ratio is left for future research.

2 The model

We build on the model by Gerali et al. (2010).[5] Our analysis starts from a well-known model for macroprudential policy analysis to have a clear benchmark against which we can assess the effects of the output floor. Figure 2 provides a simplified explanation of the model's blocks.

Figure 2: Simple description of the model



The economy is populated by patient households, impatient households and entrepreneurs. The mass of all agents in the economy is normalised to one. Households consume, accumulate housing stock and work. The two types of households differ in terms of their degree of impatience. The discount factor of patient households is higher than the one of impatient households ($\beta^P > \beta^I$). Households' heterogeneity generates positive financial flows in equilibrium, as patient households save and impatient ones borrow against the value of their housing stock.

The productive sector is composed by entrepreneurs, monopolistically competitive retailers and capital good producers. The former produce homogeneous intermediate goods using capital, and labour supplied by both types of household. To finance their capital purchases, entrepreneurs borrow from banks using their capital stock as collateral. The monopolistically competitive retailers buy intermediate goods from entrepreneurs, differentiate and price them, subject to nominal rigidities. The capital producers are a model device to introduce the price of capital.

[5]They develop a medium-scale DSGE a la Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2007) enriched by a banking sector and financial frictions. Angelini, Neri and Panetta (2014) use the same model to assess the interactions between the monetary and macroprudential policy and Gambacorta and Karmakar (2018) to assess the impact of the leverage ratio.

Finally, workers supply their differentiated labour services through unions, which set wages to maximize members' utility.

The banking sector consists of a wholesale branch and retail branches. The wholesale branch manages the capital-asset position of the bank as it accumulates bank capital out of retained earnings and pays some quadratic costs whenever it deviates from capital requirements expressed as the ratio between bank capital and RWA. Banks are subject to two different regulatory approaches to calculate RWA, banks' internal models and the output floor. Retail branches lend to impatient households and to entrepreneurs, and collect deposits from patient households. They have market power in setting lending and deposit rates.

Finally, there is a central bank that sets the policy rate according to a standard Taylor-type reaction function and a macroprudential policy authority that controls regulatory capital requirements. The latter have a steady state value and a countercylical component that depends on the credit-to-GDP ratio in the economy. This reflects the current framework in which a countercyclical capital buffer (CCyB) is placed on top of static capital requirements.

2.1 Households

Each household maximises their expected lifetime utility by choosing consumption c_t^j, housing h_t^j and labour hours l_t^j, where $j = \{P, I\}$, with P standing for patient and I for impatient households:

$$E_0 \left\{ \sum_{t=0}^{\infty} (\beta^j)^t \left[(1-a)\varepsilon_t^c \log(c_t^j - ac_{t-1}^j) + \varepsilon_t^h \log(h_t^j) - \frac{(l_t^j)^{1+\phi}}{1+\phi} \right] \right\} \tag{1}$$

where a denotes the degree of habits and ϕ the inverse Frisch elasticity of labour supply. Habits in consumption imply sluggish response of consumption to changes in real income and improve the model ability to fit data. There are two preference shocks ε_t^c and ε_t^h that affect the marginal utility of consumption and housing, respectively. All the shocks in the model follow an AR(1) specification.

Patient households. Their choices are subject to the following budget constraint, expressed in real terms:

$$c_t^P + q_t^h \Delta h_t^P + d_t = w_t^P l_t^P + \frac{(1+r_{t-1}^d)d_{t-1}}{\pi_t} + t_t^P \tag{2}$$

They spend their income on current consumption, housing (with q_t^h denoting house prices)and savings through deposits d_t.[6] The income side consists of wage earnings $w_t^P l_t^P$ (where w_t^P is the real wage) and gross interest income from deposits $\frac{(1+r_{t-1}^d)d_{t-1}}{\pi_t}$, where $\pi_t = \frac{P_t}{P_{t-1}}$ is the gross

[6]For simplicity, we assume that housing stock accumulation is continuous and without any adjustment costs, as common in DSGE model literature. Moreover, we assume that housing has a fixed supply, i.e. $h^P + h^I = 1$.

inflation rate and r^d_{t-1} denotes the interest rate on deposits. Finally, t^P_t is the lump-sum transfer that includes a labour union membership net fee, and dividends from firms and banks.

Impatient households. Their choices are subject to the following budget constraint:

$$c^I_t + q^h_t \Delta h^I_t + \frac{(1 + r^{b,H}_{t-1}) b^I_{t-1}}{\pi_t} = b^I_t + w^I_t l^I_t + t^I_t \tag{3}$$

Unlike patient households, they are willing to offer their housing wealth as collateral to obtain loans. The term $\frac{(1+r^{b,H}_{t-1})b^I_{t-1}}{\pi_t}$ indicates the payments for the previous-period loans. In the rest of this paper, we will refer to households' loans, b^I_t, also as mortgages or lending / credit to households. They must also satisfy a borrowing constraint, which imposes that the expected value of their housing stock must guarantee repayment of debt and interest, where m^I_t denotes the stochastic loan-to-value (LTV) ratio:

$$(1 + r^{b,H}_t) b^I_t \leq m^I_t E_t[q^h_{t+1} h^I_t \pi_{t+1}] \tag{4}$$

Labour supply. Patient and impatient households provide differentiated labour types, sold by unions to perfectly competitive labour packers. The wage setting is indexed to a weighted average of lagged and steady-state wage inflation. Wage stickiness allows the model to predict an inflation persistence consistent with the data and, together with price stickiness, implies that monetary policy has real effects. Details on the labour market are contained in Appendix A.

2.2 Productive sector

Entrepreneurs. Each entrepreneur maximises their expected lifetime utility by choosing consumption c^E_t:

$$E_0 \left\{ \sum_{t=0}^{\infty} (\beta^E)^t \left[\log(c^E_t - a c^E_{t-1}) \right] \right\} \tag{5}$$

subject to the budget constraint below. Entrepreneurs' expenses include consumption c^E_t, wage bills for patient ($w^P_t l^{E,P}_t$) and impatient ($w^I_t l^{E,I}_t$) households, previous-period loans repayments $\frac{(1+r^{b,E}_{t-1})b^E_{t-1}}{\pi_t}$, and capital renting expenses $q^k_t k^E_t$ (where q^k_t is the price of capital). They are financed by income from the sale of wholesale goods y^E_t (where $\frac{1}{x_t} = \frac{P^W_t}{p_t}$ corresponds to its relative competitive price) and the revenue from the undepreciated stock of capital $q^k(1-\delta)k^E_{t-1}$ sold back to capital producers. In the rest of the analysis, we will refer to entrepreneurs' loans, b^E_t, as loans to non-financial corporations (NFC) or lending / credit to firms.

$$c^E_t + w^P_t l^{E,P}_t + w^I_t l^{E,I}_t + \frac{(1 + r^{b,E}_{t-1}) b^E_{t-1}}{\pi_t} + q^k_t k^E_t = \frac{y^E_t}{x_t} + b^E_t + q^k(1-\delta)k^E_{t-1} \tag{6}$$

The wholesale good is produced according to a standard production function, $y^E_t = A_t (k^E_{t-1})^{\alpha} (l^E_t)^{1-\alpha}$ where A_t is the stochastic total factor productivity (TFP). The labour input are the sum of patient and impatient household labour supply $l_t^E = (l_t^{E,P})^{\mu}(l^{E,I})^{1-\mu}$, where μ is the proportion of labour inputs from patient households.

As for the impatient households, entrepreneurs are subject to a borrowing constraint (with m_t^E as stochastic LTV ratio) that represents a non-default condition. Indeed, the amount of funds banks are willing to lend to entrepreneurs is limited to a fraction of the discounted expected value of their capital stock:

$$(1 + r_t^{b,E})b_t^E \leq m_t^E q_{t+1}^k E_t[\pi_{t+1}(1-\delta)k_t^E] \tag{7}$$

Capital producers. A new stock of capital is produced and sold to entrepreneurs in a perfectly competitive market. Capital producers use two inputs, the previous period undepreciated capital $(1-\delta)K_{t-1}$ bought from entrepreneurs at the nominal price Q_t^k, and I_t units of the final consumption good bought from retailers at price P_t. The new stock of effective capital is sold back to entrepreneurs at price Q_t^k. The transformation of the final good into new capital is subject to adjustment costs. Details on capital producers are contained in Appendix A.

Retailers. The retail goods market is monopolistically competive (Bernanke, Gertler and Gilchrist (1999)). Retail prices are sticky and are indexed to a combination of past and steady-state inflation. Whenever retailers want to change prices beyond this indexation allowance, they face a quadratic adjustment cost. Sticky prices, together with wage stickiness, implies that monetary policy has real effects. Details on retailers are contained in Appendix A.

2.3 Banks

Each bank consists of a wholesale branch and retail branches. The wholesale branch manages the capital-asset position of the bank subject to capital requirements imposed by the macroprudential authority. Retail branches lend to impatient households, lend to entrepreneurs, and collect deposits from patient households.

Wholesale branch. Each wholesale branch operates in a perfectly competitive market. On the liabilities side, it combines wholesale deposits D_t with accumulated bank capital K_t^b, while on the assets side, it issues wholesale loans B_t^H and B_t^E to retail branches. The two sources of funding, K_t^b and D_t, are perfect substitutes. Bank capital is accumulated through retained earnings only:

$$\pi_t K_t^b = (1-\delta^b)K_{t-1}^b + \Pi_{t-1}^B \tag{8}$$

where δ^b is the cost of managing bank capital and Π_{t-1}^B denotes the realised overall profits of the bank, namely the profits of the wholesale and two retail branches. The wholesale branch is subject to risk-weighted capital requirements, meaning that it occurs in a quadratic cost whenever its capital-to-RWA ratio $\frac{K_t^b}{RWA_t^l}$ deviates from the regulatory ratio ν_t^b. The wholesale branch maximises profits taking into account these quadratic costs:

$$\max E_0 \sum_{i=0}^{\infty} \Lambda_{0,t} \Bigg[(1+R_t^{B,H})B_t^H + (1+R_t^{B,E})B_t^E - (B_{t+1}^H + B_{t+1}^E) \\ + D_{t+1} - (1+R_t^d)D_t + (K_{t+1}^b - K_t^b) - \frac{\kappa_l}{2}\left(\frac{K_t^b}{RWA_t^l} - \nu_t^b\right)^2 K_t^b \Bigg] \tag{9}$$

where κ_l measures the intensity of the quadratic costs, while the index $l \in \{IM, OF\}$ identifies the prudential approach to calculate the RWA. The above profit maximisation is subject to a balance sheet constraint in the form $B_t^H + B_t^E = K_t^b + D_t$. RWA are defined as the weighted sum of the bank's assets (i.e. B_t^H and B_t^E), where the weights, are a measure of the implicit riskiness of the different assets. In our model, banks can calculate RWA in two ways, by using their internal models or under the output floor regime.

Internal models (IM). Under this regime, risk-weighted assets are defined as following:

$$RWA_t^{IM} = (w_t^{H,IM} B_t^H + w_t^{E,IM} B_t^E) \tag{10}$$

where $w_t^{H,IM}, w_t^{E,IM}$ are the risk weights associated to mortgages and NFC loans, respectively. More specifically, we are referring to the Internal Rating Based (IRB) approach which corresponds to internal models for credit risks. The model, indeed, is able to capture only features related to the credit risks component of RWA. The IRB models' main components are the probability of default (PD) of borrowers, loss given default (LGD), exposure at default (EAD), and the maturity of the assets. In the absence of defaults in the model, we approximate the risk weights using the approach of Angelini et al. (2015). They indicate that the main characteristics of the IRB risk weights are captured by the following equation:

$$w_t^{k,IM} = (1-\rho_i)\bar{w}^{k,IM} + (1-\rho^i)\chi^i\Big(logy_t - logy_{t-4}\Big) + \rho^i w_{t-1}^k \qquad \text{with} \qquad k =\in \{H, E\} \tag{11}$$

where $\bar{w}^{k,IM}$ corresponds to the steady-state risk weights and y to the aggregate output, while $\chi^i < 0$ describes the cyclical response of the risk weights. According to this definition, risk weights tend to be low during booms and high during recessions. More details on the modelled risk weights will be given in the estimation section.

Output floor (OF). The output floor imposes that the bank's RWA calculated according to the IRB approach cannot go below 72.5% of the RWA calculated according to the standardised approach (SA):

$$RWA_t^{OF} = max\{RWA_t^{IM}, 0.725 * RWA_t^{SA}\} \tag{12}$$

where the RWA calculated under the standardised approach is defined as $RWA_t^{SA} = (w^{H,SA}B_t^H + w^{E,SA}B_t^E)$. Standardised risk weights are fixed and not exposed to the cyclical variation of risks.

Optimal wholesale rates setting. The wholesale branch's optimal problem produces a relationship between the capital position of the bank and the spread between the wholesale lending and deposit rates:

$$R_t^{B,k} - r_t = -\kappa_l \left(\frac{K_t^b}{RWA_t^l} - \nu_t^b \right) \left(\frac{K_t^b}{RWA^l} \right)^2 w_t^{k,l} \qquad \text{with } k \in \{H, E\},\ l \in \{IM, OF\} \tag{13}$$

where for the output floor $w_t^{k,OF} = max\{w_t^{k,IM} B^k, 0.725 * (w^{k,SA} B^k)\}$ indicates a sort of adjusted risk weight that comes from the definition of the RWA in equation (12).

The left-hand side of the above equations represent the marginal benefit from increasing lending of type j (an increase in profit equal to the increase in interest rate spread), while the right-hand side represents the marginal cost of doing so (an increase in the costs for deviating from ν_t^b). Therefore, the wholesale branch chooses a level of each type of lending j which, at the margin, makes the costs of changing the capital asset ratio equal to the respective benefits.

Retail branches. Retail banks are Dixit-Stiglitz monopolistic competitors on both the loan and the deposit markets. The retail branches take the loan and deposit demand schedules as given and then choose the level of interest rates to maximise profits. This modeling choice aims at introducing the interest rate stickiness observed in the actual data.

2.4 Monetary and macroprudential policy

The central bank sets the monetary policy rate r_t according to a standard Taylor rule

$$R_t = (1 - \rho_R) R + \rho_R R_{t-1} + (1 - \rho_R) \left[\phi_\pi \left(\frac{\pi_t}{\pi} \right) + \phi_y \left(\frac{Y_t}{Y} \right) \right] + \varepsilon_t^r \tag{14}$$

where $R_t = (1 + r_t)$ and ϕ_π and ϕ_y denote the weights of inflation and output, respectively. R is the steady state policy rate, ρ_R represents the persistence of the policy rate, and ε_t^r as the monetary policy shock.

The macroprudential authority sets the banks' regulatory capital-to-RWA ratio (ν_t^b) following a reaction rule as defined by Angelini et al. (2015):

$$\nu_t^b = (1 - \rho_\nu)\bar{\nu} + \rho_\nu \nu_{t-1}^b + (1 - \rho_\nu) \left[\chi_\nu \left(\frac{B_t}{Y_t} - \frac{\bar{B}}{\bar{Y}} \right) \right] \tag{15}$$

where $\bar{\nu}$ is the steady level of the capital-to-RWA ratio, namely the static component of capital requirements, while $\frac{B_t}{Y_t}$ denotes the credit-to-GDP ratio with $B_t = B_t^H + B_t^E$. The positive sensitivity of capital requirements to the credit-to-GDP, $\chi_\nu > 0$, implies the presence of a countercyclical capital buffer on top of static capital requirements.

3 Estimation

The baseline model, which assumes the IRB approach for the calculation of RWA, is estimated with Bayesian methods using eleven observables for the UK economy covering the period 1991Q1-2019Q3 at quarterly frequency.[7] The Bayesian estimation constructs the posterior distribution of the DSGE model parameters by combining the model likelihood density derived from the transformed and filtered data together with the prior distribution of the model parameters. The likelihood function is derived from the log-linear version of the model solution and using standard Kalman recursions. The posterior distribution is simulated employing the Metropolis-Hasting algorithm. Appendix C contains further details on the estimation approach.

Calibrated parameters. A subset of parameters is calibrated (see Table 4 in the Appendix C). The discount factor of patient households β^P is set at 0.9943 to pin down a 2.5% quarterly steady state shadow policy rate.[8] Meanwhile, the discount factors for impatient households and entrepreneurs, β^I and β^E, are set at 0.975 in line with the literature.[9] The calibration of the inverse Frisch elasticity ($\phi = 1.0$), capital share in the production function ($\alpha = 0.25$), and capital depreciation rate ($\delta = 0.025$) follows the literature (see Gambacorta and Karmakar (2018), among others). The steady-state loan-to-value (LTV) for household loans is set at 0.70, reflecting the average LTV ratio for mortgages used to finance house purchases in the UK in 2019. For the entrepreneurs' loans, instead, the value 0.35 is taken from the literature (Gambacorta and Karmakar (2018)). Some parameters controlling the mark-up and mark-down in the different markets are calibrated following Gerali et al. (2010). Mark-up in the goods market is set at 20% ($\epsilon^y = 6$), in the labour market at 15% ($\epsilon^l = 5$), while mark-downs for deposits at 60% ($\epsilon^d = -1.46$). The mark-up for loans to households and firms are calibrated to pin-down the share of loans to households and non-financial corporate, which are around 30% and 70%.[10]

The parameters of the prudential regimes are calibrated to match the Basel III principles,[11] and the current UK rules.[12] The cost of managing bank capital, δ^b, is calibrated to pin down

[7]These include real consumption, real investment, real house prices, real loans to households and firms, the policy rate, interest rates on deposits, loans to firms and households, real wage, and consumer price inflation rates. More details on the data are contained in the Appendix C. We decided to exclude more recent data due to the Covid-19 period which presents high non-linearities.

[8]The shadow rate is based on the computation generated by Wu and Xia (2016).

[9]See Iacoviello (2005), Gerali et al. (2010), Angelini, Neri and Panetta (2014), Hodbod, Huber and Vasilev (2018), and Gambacorta and Karmakar (2018).

[10]The proportion of households and non-financial corporate loans are based on a quarterly average for the period 1991Q1-2019Q3.

[11]See *Basel III: A global regulatory framework for more resilient banks and banking systems*; `https://www.bis.org/publ/bcbs189.htm`.

[12]See *Supplement to the December 2015 Financial Stability Report: The framework of capital requirements*

a leverage ratio $\frac{K^b}{B}$ of 4%. The steady state capital requirements ν^b is set equal to 9%, which is the average of the (fixed) capital requirements in the UK.[13] The cost of deviating from the capital requirements with internal models ($\kappa_{IM} = 15$) and the output floor ($\kappa_{OF} = 10$) are calibrated to pin down the same steady state level of capital-to-RWA ratio ($\frac{K^b}{RWA} = 9\%$).

Estimation results. We mostly use the priors in Gerali et al. (2010). But our posteriors show some differences compared to the results using European data. For instance, most of the exogenous processes have higher persistence in the UK than the Euro Area. These results are broadly consistent with previous DSGE estimates conducted for the UK economy by DiCecio and Nelson (2007), Harrison and Oomen (2010) and Villa and Yang (2012). Notably, the technology shock is more persistent in the UK than in the Euro Area (0.97 vs 0.94).[14] Similarly, the degree of consumption habits is estimated to be higher in the UK (0.94) than in the Euro Area (0.86).

Moreover, we find that wage rigidities are stronger than price stickiness, consistent with Gerali et al. (2010). For the monetary policy rule, we estimate the response to inflation at 2.03 and policy rate persistence equal to 0.87. Both values are in line with the findings of DiCecio and Nelson (2007). Meanwhile, we estimate the coefficient measuring the response to output growth equal to 0.27, which is slightly higher than the previous estimates of DiCecio and Nelson (2007) and Harrison and Oomen (2010) that estimated the output growth coefficient at 0.05 and 0.12, respectively. Regarding the financial variables, we find results similar to those of Gerali et al. (2010). In particular, we find that the degree of stickiness of UK loan rates (determined by κ_{bH} and κ_{bE}) are similar to those of the Euro Area. Moreover, the estimation shows that deposit rates adjust more rapidly than loan rates to changes in the policy rate in the UK. Table 5 in Appendix C contains the values of all estimated parameters.

Risk weights. Table 2 summarises the calibration of the risk weights functions. Standardised (SA) risk weights and steady state values of the internally modelled (IM) risk weights are calibrated using data on UK banks. The parameters controlling the sensitivity and persistence of IM risk weights are set following Angelini, Neri and Panetta (2014).[15]

Table 2 provides us with some indications of key static and dynamic properties of risk weights. First, in the steady state, the risk weight of NFC loans is higher than the mortgage risk weight (0.57 vs 0.16), reflecting a higher implicit riskiness of the former compared to the

for UK banks; `https://www.bankofengland.co.uk/-/media/boe/files/financial-stability-report/2015/supplement-december-2015.pdf`.

[13] The value of 9% considers the minimum capital requirements (4.5%) plus the Pillar 2A requirements and capital buffers, in CET1 capital space.

[14] Villa and Yang (2012) estimated a persistence of technology shock for the UK at 0.98 while Harrison and Oomen (2010) estimated it at 0.99.

[15] We were not able to estimate sensitivity and persistence of modelled risk weights given very limited availability of data.

Table 2: Risk Weights

Parameter	Value	Definition	Source
$w^{H,SA}$	0.30	SA risk weight on mortgages	Calibrated on UK data
$w^{E,SA}$	0.70	SA risk weight on NFC loans	Calibrated on UK data
$w^{H,IM}$	0.16	Steady-state IM risk weight on mortgages	Calibrated on UK data
$w^{E,IM}$	0.57	Steady-state IM risk weight on NFC loans	Calibrated on UK data
$\chi_{w^{E,IM}}$	-10	Sensitivity of IM risk weights (NFC loans)	Angelini, Neri and Panetta (2014)
$\chi_{w^{H,IM}}$	-15	Sensitivity of IM risk weights (mortgages)	Angelini, Neri and Panetta (2014)
$\chi_{w^{E,IM}}$	0.92	Persistence of IM risk weights (NFC loans)	Angelini, Neri and Panetta (2014)
$\chi_{w^{H,IM}}$	0.94	Persistence of IM risk weights (mortgages)	Angelini, Neri and Panetta (2014)

latter. The gap between the risk weights means also that mortgages have a lower cost for banks in terms of capital requirements. Second, the risk weights have different cyclical properties, and, in particular, the risk weights for mortgages react more to changes in economic conditions, which is line with the highest cyclicality of models used for those risk weights.

Finally, Table 2 shows us that in steady state, mortgages have a larger IM-SA gap compared to NFC loans. The modelled risk-weight for mortgages is 53.3% of the standardised one, while the modelled risk-weight for NFC loans is 81.4% of the standardised one. Therefore, we expect that under a binding output floor, banks will have incentives to prefer NFC loans at the margin compared to mortgages. However, the dynamics of the risk weight gaps depend also on the reactions of the internally-modelled risk weights to GDP fluctuations. So, we will come back to this point in Section 4.

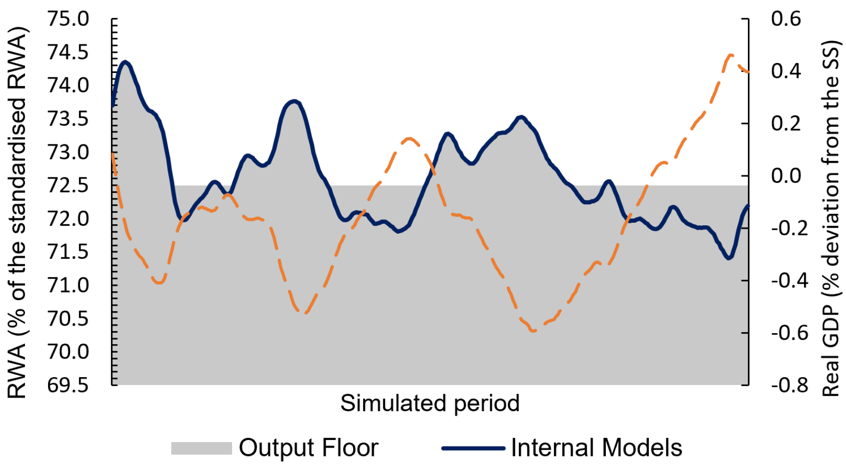
4 Model Analysis

This section evaluates how the output floor influences macro-financial dynamics within the model, comparing outcomes under two regulatory regimes: internally modelled risk weights and the output floor. Using the calibrated and estimated parameters, we assess the output floor's cyclical behaviour, its effect on key variables such as lending and RWA, and its implications for macroprudential policy.

4.1 Dynamics of the output floor

We begin by examining how the output floor behaves over the economic cycle. Figure 3 shows that the floor is most likely to bind during economic expansions or when the economy is recovering from a downturn.[16] This occurs because internally modelled risk weights fall during upswings, reflecting lower measured credit risk, and pulling modelled RWA downwards. The output floor prevents these declines from becoming excessive by setting a minimum level of RWA based on the standardised approach. As a result, the output floor acts as a stabilising mechanism: it reduces the volatility of RWA over time, limits the extent to which capital requirements fall during booms, and provides a more predictable regulatory constraint throughout the cycle.

Figure 3: Simulation of RWA and Real GDP



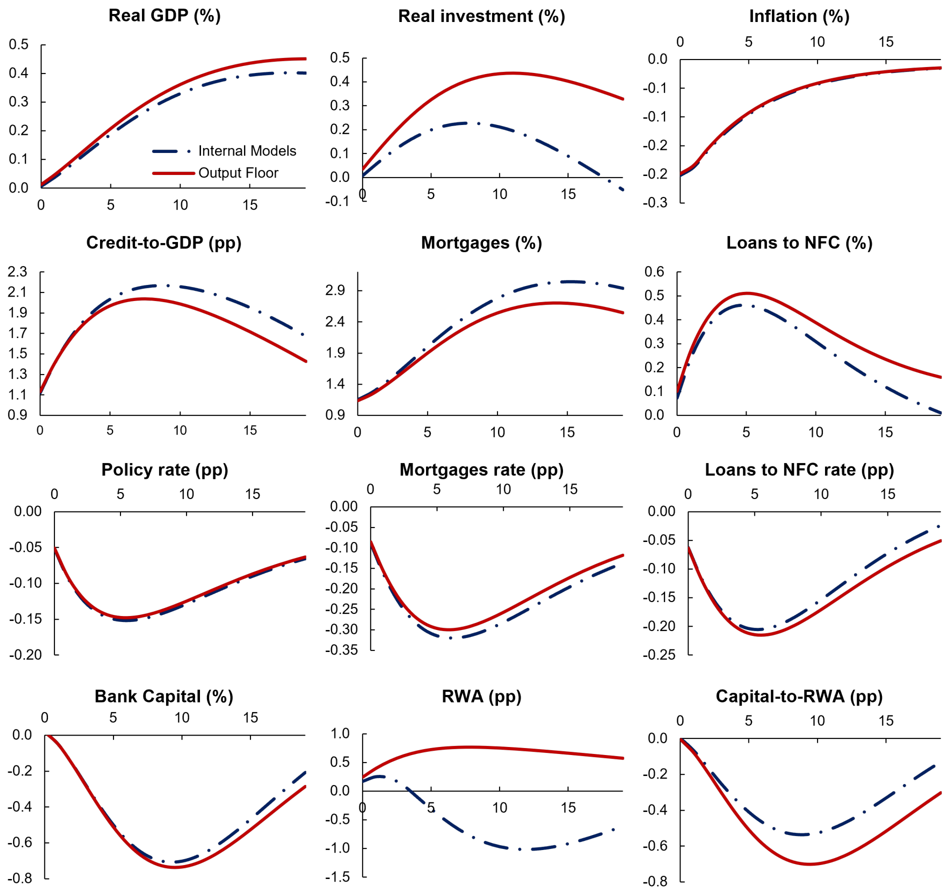
[16]The output floor prevents these downward pressures, by setting a floor to the reduction of RWA. The aggregate nature of the analysis does not allow us to assess the impact of the output floor at bank-level. Therefore, this result does not exclude the possibility that for some banks, for instance those banks largely exposed to assets with a large IM-SA gap, the output floor is always binding, including during a downturn.

4.2 Impulse Response Functions

To analyse the output floor's effects further, we examine the model's impulse responses to two shocks: a positive technology (TFP) shock, and an increase in firms' loan-to-value (LTV) ratios.

Technology shock. Figure 4 shows that positive TFP shock raises output, investment, and lending. The capital requirements aim to mitigate the build-up of credit but the magnitude of their effects depends on how the RWA are calculated.

Figure 4: IRFs to a positive TFP shock[17]



After the shock, the banks' capital-to-RWA ratio falls because RWA, affected by both the increase in lending and the sensitivity of risk weights to economic conditions, rises more quickly than bank capital. This deviation from the regulatory capital-to-RWA ratio imposes costs on banks, which, in turn, are incentivised to expand lending less than they would in the absence of such regulation.

[17]IRFs of real GDP, real investment, inflation, loans, bank capital and RWA are expressed in percentage deviations from the steady state. While, IRFs of credit-to-GDP, policy rate, loans rate and capital-to-RWA are in absolute deviations from the respective steady state and expressed in percentage points.

These incentives are stronger with the output floor rather than under the internal-models regime. Following the shock, the fall in modelled risk weights (see Figure 12 in Appendix B) mitigates the increase in RWA. However, under the output floor regime this effect is dampened because the downward pressure on risk weights is capped at 72.5% of their standardised value. As a result, the fall in banks' capital-to-RWA ratios - and therefore the associated regulatory costs - is greater under the output floor. Banks are consequently incentivised to restrict more the credit expansion triggered by the TFP shock in order to limit these costs. The resulting increase in the credit-to-GDP ratio is therefore more muted when the output floor is in place.

Figure 4 highlights another important effect of the output floor, namely an asymmetric impact across assets: the output floor mitigates the rise in mortgage lending but amplifies the expansion in corporate lending. As discussed in the introduction, the gap between internally modelled and standardised (IM-SA) risks weight across asset classes drives this result. Over the 20 periods following the shock, the modelled risk weight for mortgages averages 53% of its standardised equivalent, while the modelled risk weight for corporate loans averages 81% (see Figure 14 in Appendix D). Consequently, under the output floor, the marginal contribution of mortgages to aggregate RWA - that is, the increase in RWA when an additional unit of mortgages is extended - is larger than under the internal-models approach, while the opposite holds for corporate loans.

Figure 5: Marginal contribution of assets to RWA: OF vs IRB[18]

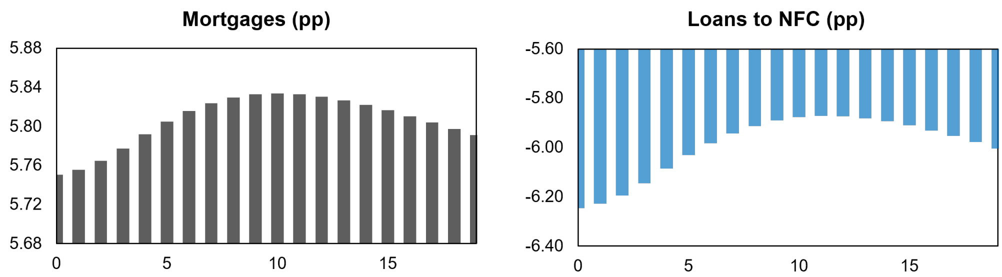


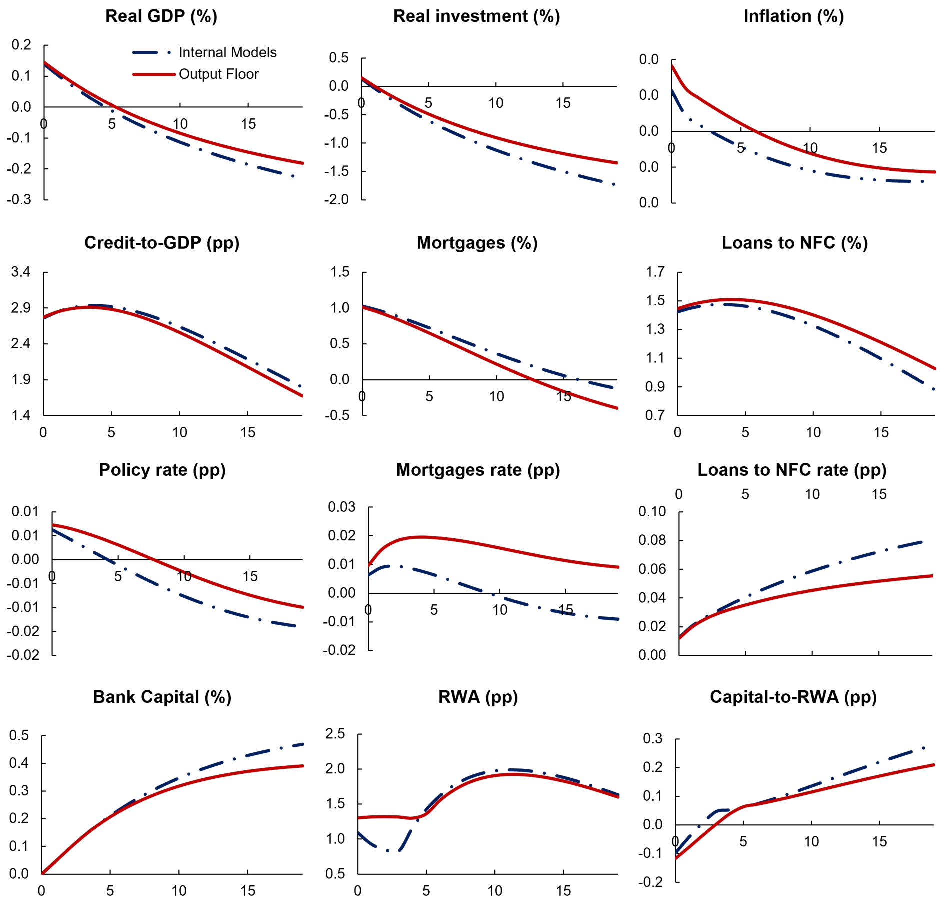
Figure 5 shows the difference between the output floor-implied risk weights and the internally modelled ones over the simulated period. This illustrates how the marginal contribution of each asset class to aggregate RWA differs under the two prudential regimes. The difference is positive for mortgages but negative for NFC loans. This indicates that, under the output floor, mortgages become marginally more expensive in terms of capital requirements, while NFC loans become marginally less expensive. At the margin, banks have an incentive to expand their NFC lending

[18]The figure reports the difference between the output floor-implied risk weight and the IM risk weight for both assets - i.e. $\Delta w^k = (0.725 * (w^{k,SA}) - w^{k,IM}) * 100 \quad \text{with} \quad k \in \{Mortgages,\ Loans\ to\ NFC\}$ - after a positive TFP shock. The variables are expressed in percentage points.

when the output floor binds.

The asymmetric response of mortgages and corporate loans implies that the overall effect of the output floor on aggregate credit-to-GDP is mild. The stronger expansion in lending to NFCs is largely offset by the weaker increase in mortgage lending, which dampens the aggregate credit response. However, because corporate lending in the model is used directly for productive activity, this reallocation leads to higher real GDP and investment at the aggregate level under the output floor compared with the internal-models case.

Figure 6: IRFs to a positive LTV ratio shock[19]



LTV ratio shock. Figure 6 shows that a positive shock to LTV ratio increases firms' borrowing capacity and, in turn, boosts banks' profits. These dynamics generate a temporary economic expansion. Modelled risk weights initially decline in response to the rise in GDP (Figure 15 in Appendix D), causing the output floor to bind in the first few periods. As in the case of the TFP shock, the output floor more effectively restrains the expansion of credit-to-GDP than

[19]The impulse responses of real GDP, real investment, inflation, loans, bank capital and RWA are in percentage deviations from steady state. The responses of credit-to-GDP, policy rate, loans rate and capital-to-RWA are in absolute deviations from the respective steady state levels, and expressed in percentage points.

the internal-models regime and alters the composition of lending between households and firms. In particular, the output floor makes the increase in NFC lending more persistent, while the opposite occurs for mortgages. This reallocation implies a longer-lasting rise in real investment and real GDP.

4.3 Macroprudential authority objective

Finally, we assess how the implementation of the output floor affects the objectives of the macroprudential authority.[20] To do this, we compute the loss function of the macroprudential authority, following Angelini, Neri and Panetta (2014). The macroprudential authority aims to minimise the volatility of the credit-to-GDP ratio (B/Y) and, when relevant, the volatility of real GDP (Y):

$$L = \sigma^2_{B/Y} + \kappa_Y \sigma^2_Y + \kappa_{\nu^b} \sigma^2_{\Delta^b_\nu} \tag{16}$$

where σ_i^2 represents the asymptotic variance of the target variables, while parameters $\kappa_Y \geq 0$ and $\kappa_{B/Y} \geq 0$ represent the policymaker's preferences over real GDP and credit-to-GDP). As highlighted by Angelini, Neri and Panetta (2014), a positive κ_{ν^b} is important to ensure that the policy instrument (ν^b, defined in equation 15) is not too volatile.

Table 3 reports the key standard deviations and the values of the macroprudential authority's loss functions obtained by simulating a series of technology shocks and LTV ratio shocks for the model under both the internal-models and the output floor regime.

Technology shocks. The standard deviation of all variables considered - except for real GDP - is lower under the output floor regime. In particular, the output floor substantially reduces the volatility of the credit-to-GDP ratio (by 12%) and of RWA (by 20%). The higher standard deviation of real GDP, by contrast, reflects the portfolio reallocation discussed earlier. As shown in Figure 4, the output floor leads to a larger expansion of real investment and real GDP during an economic boom. Turning to the loss functions, the output floor materially lowers the macroprudential authority's loss, regardless of the weight placed on the real GDP volatility: -23% when $\kappa_Y = 0$; and -18% when $\kappa_Y = 0.5$.

LTV ratio shocks. In this case, the output floor is even more effective at reducing standard deviations. As in the previous scenario, it lowers the volatility of both the credit-to-GDP ratio and RWA, fully in line with its intended purpose. It also supports the macroprudential authority's objectives by reducing its loss function.

Overall, the output floor is highly effective in helping the macroprudential authority achieve its objectives. It materially reduces the volatility of the credit-to-GDP ratio by limiting the

[20] With this model, we could have considered the monetary authority objectives as well. But the study of the interaction between the output floor and the monetary policy is beyond the scope of this paper.

excessive variability of RWA. Our analysis also shows that the output floor dampens the time-series volatility of RWA itself, and this reduction feeds through to lower volatility in several other macro-financial variables. This is a novel and important result, with potential implications for stress-testing and prudential policy. For example, if RWA fluctuate less following the onset of adverse shocks, the capital impact of those shocks may also be more muted.

Table 3: Standard Deviations and Loss Functions[21]

	Standard deviations (%)				Loss Functions (% change wrt IM)	
	Y	B/Y	$\Delta\nu^b$	RWA	$\kappa_Y = 0$	$\kappa_Y = 0.5$
	Technology (TFP) shocks					
Internal Models (IM)	2.09	4.19	2.36	4.48	–	–
Output Floor	2.44	3.68	2.09	3.57	-22.9	-6.5
	LTV ratio shocks					
Internal Models (IM)	3.16	6.40	3.46	14.23	–	–
Output Floor	2.75	5.76	3.10	11.09	-18.8	-19.4

5 Conclusions

We develop a DSGE framework featuring a two-asset banking sector, financial frictions, sticky interest rates and multiple regulatory constraints to assess the macroeconomic effects of the output floor, a new prudential standard introduced as part of the Basel III reforms.

Our results highlight three main findings. First, the output floor reduces the increase in the credit-to-GDP ratio during economic expansions - such as those triggered by positive technology or LTV ratio shocks - because it tightens banks' capital constraints relative to a regime based solely on internal-model risk weights. Second, the output floor induces portfolio reallocation. Banks are incentivised to shift towards assets with a relatively small IM-SA gap and away from those where the IM-SA gap is larger. Using UK data, we find that during an expansion the output floor dampens the growth of mortgage lending while amplifying the expansion of credit to NFCs. Third, the output floor supports macroprudential objectives by reducing the time-series volatility of RWA and, in turn, the volatility of the credit-to-GDP ratio.

[21] The table reports the standard deviations in percentage points and the difference between the authorities' loss function under internal models and the output floor. The % change of the loss functions are calculated as $\left(\frac{LF_{IM}}{LF_{OF}} - 1\right) * 100$.

These findings have several policy implications. Most importantly, the output floor reduces the procyclicality of capital requirements and lending created by the excessive responsiveness of internal models to economic and financial conditions. This supports its inclusion in the policy toolkit as an effective means of addressing the limitations of model-based regulation. At the same time, the induced portfolio shifts imply that policymakers should consider potential distributional consequences for the real economy and the implications for banks' risk profiles. In addition, our analysis suggests that the output floor reduces the cyclical variability of RWA and of a range of macro-financial variables. This is a novel and policy-relevant result, which may have implications for the design of stress tests and the calibration of macroprudential tools.

There are several avenues for future research. The leverage ratio requirement also aims to limit the understatement of asset risk. Incorporating the leverage ratio into the model would therefore be a natural extension and would allow a richer assessment of how the two regulatory tools interact. Finally, while the model assumes an established functional form for internally modelled risk weights, a more micro-founded rationale for their cyclical behaviour would further enhance understanding of how the output floor influences banks' portfolio choices.

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A Appendix A. Model

This Appendix contains more details on some model's blocks that are only briefly described in the body of the paper.

Labour market. For each labour type m there are two unions, one for patient households and one for impatient households (indexed by s, where $s = P, I$). Unions set nominal wages $W_t^s(m)$ maximising the utility of their members, subject to the labour packers demand and to a quadratic adjustment cost (parametrised by κ_w).

$$E_0 \sum_{t=0}^{\infty} (\beta^s)^t \left\{ U_{c_t^s}(i,m) \left[\frac{W_t^s(m)}{P_t} l_t^s(i,m) - \frac{\kappa_w}{2} \left(\frac{W_t^s(m)}{W_{t-1}^s(m)} - \pi_{t-1}^{\iota_w} \pi^{1-\iota_w} \right)^2 \frac{W_t^s}{P_t} \right] - \frac{l_t^s(i,m)^{1+\phi}}{1+\phi} \right\}$$

The wage setting is indexed to a weighted average of lagged and steady-state wage inflation, where ι_w indicates the wedge. The demand from labour packers has a standard CES representation $l_t^s(i,m) = l_t^s(m) = \left(\frac{W^s(m)}{W_t^s} \right)^{-\varepsilon_t^l} l_t^s$. In a symmetric equilibrium, labour supply for a household of type s is given by:

$$\kappa_w(\pi_t^{w^s} - \pi_{t-1}^{\iota_w} \pi^{1-\iota_w}) \pi_t^{w^s} = \beta_t E_t \left[\frac{\lambda_{t+1}^s}{\lambda_t^s} \kappa_w (\pi_{t+1}^{w^s} - \pi_t^{\iota_w} \pi^{1-\iota_w}) \frac{(\pi_{t+1}^{w^s})^2}{\pi_{t+1}} \right] + (1-\varepsilon_t^l) l_t^s + \frac{\varepsilon_t^l l_t^{s1+\phi}}{w_t^s \lambda_t^s} \tag{17}$$

where, for each type, w_t^s is the real wage and $\pi_t^{w^s}$ is nominal wage inflation.

Capital producers. The capital producers' maximization problem is given by:

$$E_0 \left\{ \sum_{t=0}^{\infty} \Lambda_t^E (\beta^E)^t \left[q_t^k (k_t - (1-\delta) k_{t-1}) - I_t \right] \right\} \tag{18}$$

subject to the law of motion of capital $k_t = (1-\delta)k_{t-1} + \left[1 - \frac{\kappa_i}{2} \left(\frac{\varepsilon_t^{qk} I_t}{I_{t-1}} - 1 \right)^2 \right] I_t$, where $q_t^k \equiv \frac{Q_t^k}{P_t}$ the real price of capital and ε_t^{qk} denotes a shock to investment efficiency with an AR(1) representation $log(\varepsilon_t^{qk}) = \rho_{qk} log(\varepsilon_{t-1}^{qk}) + \sigma_t^{qk}$. In equilibrium $k_t^E = k_t$.

Retailers. Each retailer chooses P_t subject to the consumers' demand function:

$$E_0 \left\{ \sum_{t=0}^{\infty} \Delta_{0,t}^P \left[\left(P_t(i) y_t(i) - P_t^W y_t(i) - \frac{\kappa_p}{2} \left(\frac{P_t(i)}{P_{t-1}(i)} - \pi_{t-1}^{i_p} \pi^{1-i_p} \right)^2 P_t y_t \right) \right] \right\} \tag{19}$$

where the CES demand function is given by $y_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\varepsilon_t^y} y_t$ where π denotes the steady state inflation, and ε_t^y the stochastic demand price elasticity, which follows an AR(1) process $log(\varepsilon_t^y) = (1-\rho_y)\bar{\varepsilon}^y + \rho_y log(\varepsilon_{t-1}^y) + \sigma_t^y$ (where $\bar{\varepsilon}^y$ denotes the steady-state markup in the goods market).

Retail banks. The loan and deposit demand schedules facing bank j are defined as:

$$b_t^s(j) = \left(\frac{r_t^{bs}(j)}{r_t^{bs}} \right)^{-\varepsilon_t^{bs}} b_t^s, \qquad d_t^P(j) = \left(\frac{r_t^d(j)}{r_t^d} \right)^{-\varepsilon_t^d} d_t \qquad \text{with} \qquad s \in \{H, E\} \tag{20}$$

where ε_t^{bs} and ε_t^d, $(s = H, E)$, are elasticities of loan and deposit demand. Elasticities are stochastic and their innovations can be interpreted as innovations to bank spreads arising independently of monetary policy.

The loan retailers maximise their profits subject to the loan demand schedule:

$$\max_{r_t^{B,H}, r_t^{B,E}} E_0 \sum_{i=0}^{\infty} \Lambda_{0,t} \Bigg[r_t^{B,H}(j) b_t^H(j) + r_t^{B,E}(j) b_t^E(j) - (R_t^{B,H} B_t^H(j) + R_t^{B,E} B_t^E(j)) \\ - \frac{\kappa_{bH}}{2} \left(\frac{r_t^{bH}(j)}{r_{t-1}^{bH}(j)} - 1 \right)^2 r_t^{bH} b_t^H - \frac{\kappa_{bE}}{2} \left(\frac{r_t^{bE}(j)}{r_{t-1}^{bE}(j)} - 1 \right)^2 r_t^{bE} b_t^E \Bigg] \tag{21}$$

The first two terms are the returns from lending to households and entrepreneurs. The next term reflects the cost of remunerating funds received from the wholesale branch. The last two terms are the costs of adjusting the interest rates. After imposing a symmetric equilibrium, the first-order conditions for interest rates yields:

$$1 - \varepsilon_t^{bs} + \varepsilon_t^{bs} \frac{R_t^{bs}}{r_t^{bs}} - \kappa_{bs} \left(\frac{r_t^{bs}}{r_{t-1}^{bs}} - 1 \right) \frac{r_t^{bs}}{r_{t-1}^{bs}} + E_t \left[\Lambda_{t+1}^P \kappa_{bs} \left(\frac{r_{t+1}^{bs}}{r_t^{bs}} - 1 \right) \left(\frac{r_{t+1}^{bs}}{r_t^{bs}} - 1 \right)^2 \frac{B_{t+1}^s}{B_t^s} \right] = 0 \tag{22}$$

The discount factor is equal to the one of the patient households because they own the banks. It can be seen that retail rates depend on the markup and on the wholesale rate (the marginal cost for banks), which in turn depends on the bank's capital position and the policy rate.

A similar equation can be derived for the deposit retail branch:

$$-1 - \varepsilon_t^d + \varepsilon_t^d \frac{r_t}{r_t^d} - \kappa_d \left(\frac{r_t^d}{r_{t-1}^d} - 1 \right) \frac{r_t^d}{r_{t-1}^d} + E_t \left[\Lambda_{t+1}^P \kappa_d \left(\frac{r_{t+1}^d}{r_t^d} - 1 \right) \left(\frac{r_{t+1}^d}{r_t^d} - 1 \right)^2 \frac{d_{t+1}}{d_t} \right] = 0 \tag{23}$$

Finally, the total profits of the banking group, j, can be written as follows:

$$\Pi_t = r_t^{BH} b_t^H + r_t^{BE} b_t^E - r_t^d d_t - \frac{\kappa_l}{2} \left(\nu_t^b - \frac{K_t^b}{RWA_t^l} \right)^2 K_t^b - \\ \frac{\kappa_{bH}}{2} \left(\frac{r_t^{bH}(j)}{r_{t-1}^{bH}(j)} - 1 \right)^2 r_t^{bH} b_t^H - \frac{\kappa_{bE}}{2} \left(\frac{r_t^{bE}(j)}{r_{t-1}^{bE}(j)} - 1 \right)^2 r_t^{bE} b_t^E \tag{24}$$

Market clearing and shock processes. The aggregate output in the economy is divided into consumption, accumulation of physical and bank capital, and the various adjustment costs:

$$Y_t = C_t + I_t + \delta^b \frac{K_{t+1}^b}{\pi_t} + Adj_t \tag{25}$$

where $C_t = c_t^P + c_t^I + c_t^E$ is aggregate consumption, I_t is aggregate investment undertaken, and K_{t+1}^b is aggregate bank capital. The $Adjt$ includes all adjustment costs.

The model has x shocks $\{A\}$. All of them follow an AR(1) specification:

B Appendix B. Model solution

The baseline model, which features the IRB method for the calculation of the RWA, is solved using algorithm developed in Dynare (Adjemian et al. (2011)). To solve the model with the output floor which features a non-differentiable function, instead, we adopted the Holden (2016) toolbox or DynareOBC that allows the calculation of a second-order pruned perturbation approximation and that supports 'max functions'. Moreover, since we have a second-order solution to the underlying model, we can capture the precautionary effects stemming from the model's nonlinearities.[22] The algorithm is applied to the solution of general non-linear models, allowing for future uncertainty. The approach generalises to higher orders that improve accuracy away from the steady-state as well as capturing important risk channels. Below is a summary of the solutions method:[23]

Suppose that $x_0 \in \mathbb{R}^n$ and that $f : \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}^c \times \mathbb{R}^m \to \mathbb{R}^n$, $g, h : \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}^c \times \mathbb{R}^m \to \mathbb{R}^c$ are given continuously $d \in \mathbb{N}^+$ times differentiable functions. Find $x_t \in \mathbb{R}^n$ and $r_t \in \mathbb{R}^c$ for all $t \in \mathbb{N}^+$:

$$0 = E_t f(x_{t-1}, x_t, x_{t+1}, r_t, \varepsilon_t)$$
$$r_t = E_t \ \max\{h(x_{t-1}, x_t, x_{t+1}, r_t, \varepsilon_t), g(x_{t-1}, x_t, x_{t+1}, r_t, \varepsilon_t)\}$$

where $\varepsilon \sim NIID(0, \Sigma)$, where the max operator acts elementwise on vectors, and where the information set is such that for all $t \in \mathbb{N}^+$, $E_{t-1}\varepsilon = 0$ and $E_t\varepsilon_t = \varepsilon_t$. To deal with non-linearity other than the bounds. In the above problem set up, there exist $\mu_x \in \mathbb{R}^n$ and $\mu_r \in \mathbb{R}^c$ such that:

$$0 = f(\mu_x, \mu_x, \mu_x, \mu_r, 0)$$
$$\mu_r = \max\{h(\mu_x, \mu_x, \mu_x, \mu_r, 0), g(\mu_x, \mu_x, \mu_x, \mu_r, 0)\}$$

and such that for all $\alpha \in \{1, ..., c\}$, $(h(\mu_x, \mu_x, \mu_x, \mu_r, 0))_\alpha \neq (g(\mu_x, \mu_x, \mu_x, \mu_r, 0))_\alpha$.

[22] Higher-order approximations provide a better fit to the model's non-linearities, but they also have important implications for how risk affects model dynamics. At first order, certainty equivalence holds and there is no risk premium; at second order, risk is constant; and at third order, risk is linear in the state and is the lowest order at which it will be time varying.

[23] The algorithm is implemented in the DynareOBC toolkit, which extends Dynare to solve models featuring inequality constraints. This is available at `https://github.com/tholden/dynareOBC`. Holden (2016) provides the theoretical foundations for this method.

C Appendix C. Estimation

This Appendix contains more details on the model estimation: data, estimation methodology, results and convergence test.

Data definition and sources. The model is estimated with Bayesian techniques using eleven key macroeconomic quarterly UK time series. All data are seasonally adjusted and demeaned. The original data the relative transformation are summarised below. [24] While Figure 7 shows the historical and smoothed variables.

- **Consumption.** Data: nominal private final consumption expenditure (in million British Pounds), quarterly, seasonally adjusted. Transformation: deflated by GDP implicit price deflator and divided by population index, first log difference x 100. Source: Federal Reserve Economic Data (FRED).

- **Investment.** Data: gross fixed capital formation (in million British Pound), quarterly, seasonally adjusted. Transformation: deflated by GDP implicit price deflator and divided by population index, first log difference x 100. Source: FRED.

- **House prices.** Data: real residential property prices for the UK (percent per annum), not seasonally adjusted. Transformation: divided by four to convert to quarterly series. Source: FRED.

- **Wages.** Data: unit labour cost, total labour productivity for the UK, index 2015=100, quarterly, seasonally adjusted. Transformation: deflated by GDP deflator, first log difference x 100. Source: FRED.

- **Inflation.** Data: GDP implicit price deflator, index 2015=100, quarterly, seasonally adjusted. Transformation: first log difference x 100. Source: FRED.

- **Policy rate.** Data: shadow rate for the UK (percent per annum) computed following Wu and Xia (2016). Transformation: divided by four to convert to quarterly series. Source: Wu and Xia (2016).

- **Deposit rate.** Deposit rate in the UK (percent per annum). Transformation: divided by four to convert to quarterly series. Source: FRED.

- **Households borrowing rate.** Data: household personal loan rate in the UK (percent per annum), not seasonally adjusted. Transformation: divided by four to convert to quarterly series. Source: FRED.

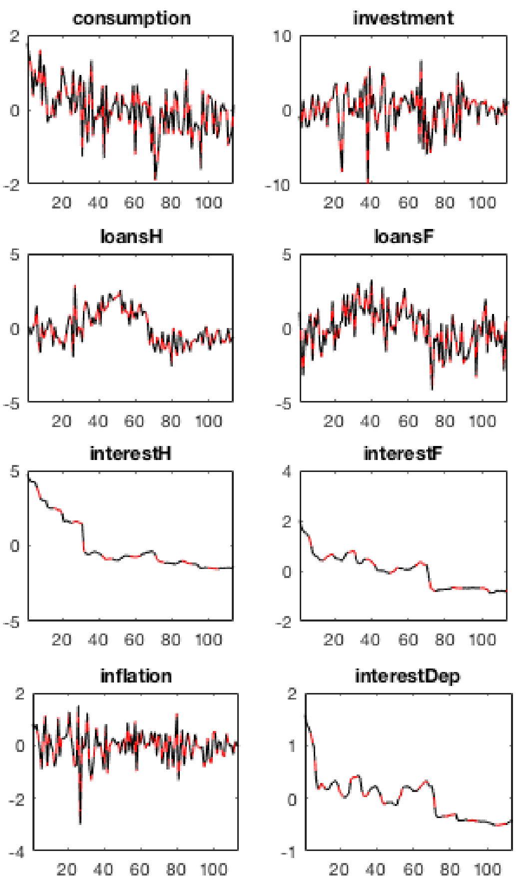
[24] For the data transformation we mostly followed Smets and Wouters (2007).

- **Firms borrowing rate.** Data: corporate borrowing rate on loans from banks in the UK (percent per annum), not seasonally adjusted. Transformation: divided by four to convert to quarterly series. Source: FRED.

- **Households borrowing volumes.** Data: quarterly lending secured on dwellings, amount outstanding (in million British Pounds), seasonally adjusted. Transformation: deflated by GDP implicit price deflator, first log difference x 100. Source: Bank of England (BoE) database.

- **Firms borrowing volumes.** Data: quarterly credit to non-financial sector (in million British Pounds), not seasonally adjusted. Transformation: deflated by GDP implicit price deflator, first log difference x 100. Source: Federal Reserve Economic Data (FRED) and Bank for International Settlements (BIS).

Figure 7: Historical and Smoothed Variables



Estimation methodology. Empirical macroeconomics practice is to use Bayesian approach to the replace informal moment matching with formal systems estimation. Maximum Likelihood (ML), General Method of Moments (GMM) and Bayesian estimation are three widely used systems estimation methods for DSGE models. We use a Bayesian approach for several reasons. First, these procedures, unlike full information maximum likelihood, for example, allow us to use prior information to identify key structural parameters. In addition, the Bayesian methods employed here utilize all the cross-equation restrictions implied by the general equilibrium set-up, which makes estimation more efficient when compared to partial equilibrium approaches. Moreover, Bayesian estimation and model comparison are consistent even when the models are misspecified, as shown by Fernandez-Villaverde and Rubio-Ramirez (2004). Finally, this framework provides a straightforward method of evaluating the ability of the models in capturing the cyclical features of the data, while allowing for a fully structural approach to analyze the sources of fluctuations.

DSGE models focus on explaining business cycle fluctuations around steady state values: model solutions imply stationarity of the variables. However, actual macro data exhibits both trends and cycles, therefore it is sometimes necessary to transform the data in order to fit properties of the model. Once trends have been satisfactorily removed, one can then focus on cyclical behaviour. DSGE models are currently estimated with a two-step approach: data is first detrended/filtered and then structural parameters are estimated.

Bayesian analysis requires initial information, hence we specify the prior distribution of the structural parameters to be estimated. We then input the transformed and filtered data to observe the likelihood density or the probability of observing the data given the model and parameters. Given the prior and likelihood, and applying the Bayes theorem, we are then able to extract the posterior distribution with confidence intervals for parameters estimated. The posterior distribution also provides information regarding identification of parameters - how much information does the data provide on parameters.

The Bayesian approach uses the log-linear approximation of the original model's non-linear optimality conditions around a non-stochastic steady state, obtaining a linear rational expectations system, which is then solved for the state-space form in its predetermined variables. Subsequently, standard Kalman recursions are applied to compute the likelihood function which, combined with the prior assumptions about model parameters to be estimated, allows us to evaluate their posterior probability. The choice of priors for the estimated parameters is usually determined by the theoretical implications of the model and evidence from previous studies. Our aim is to find the posterior distribution that summarises what we know about the parameters such as posterior means and standard deviations.

Calibrated parameters. Table 4 contains the value of the calibrated parameters.

Estimated parameters. Table 5 describe how we set the prior for the estimated parameters and the estimation results (mean, medina and confidence intervals).

Table 4: Calibrated parameters

Parameter	Value	Definition	Source
β^P	0.9943	Patient households' discount factor	Steady-state $R = 2.5\%$
β^I	0.975	Impatient households' discount factor	Iacoviello (2005)
β^E	0.975	Entrepreneurs' discount factor	Iacoviello (2005)
ϕ	1.00	Inverse of the Frisch elasticity	Gerali et al. (2010)
ε^y	6.00	Markup in the goods market $\left(\frac{\varepsilon^y}{\varepsilon^y-1}\right)$	Gerali et al. (2010)
ε^l	5.00	Markup in the goods market $(\frac{\varepsilon^l}{\varepsilon^l-1})$	Gerali et al. (2010)
ϵ^d	-1.46	Markdown in the deposits market $(\frac{\varepsilon^d}{\varepsilon^d-1})$	Gerali et al. (2010)
$\epsilon^{b,H}$	2.79	Markup on loans to households $(\frac{\epsilon^{b,H}}{\epsilon^{b,H}-1})$	Steady-state $\frac{B^H}{B} = 30\%$
$\epsilon^{b,E}$	3.12	Markup on loans to entrepreneurs $(\frac{\epsilon^{b,E}}{\epsilon^{b,E}-1})$	Steady-state $\frac{B^E}{B} = 70\%$
α	0.25	Capital share in the production function	Gerali et al. (2010)
γ^P	0.50	Share of patient household	Brzoza-Brzezina, Kolasa and Makarski (2013)
γ^I	0.25	Share of impatient household	Brzoza-Brzezina, Kolasa and Makarski (2013)
γ^E	0.25	Share of entrepreneurs	$1 - \gamma^P - \gamma^I$
δ	0.025	Capital depreciation rate	Gerali et al. (2010)
m^I	0.70	LTV ratio for impatient households	calibrated on UK data
m^E	0.35	LTV ratio for entrepreneurs	Gerali et al. (2010)
δ^b	0.25	Cost of managing bank capital	Steady-state $\frac{K^b}{B} = 4\%$
ν^b	0.09	Steady-state capital requirements	Basel III & UK regulation
κ_{IM}	15	Cost of deviating from capital requirements	Steady-state $\frac{K^b}{RWA^{IM}} = 9\%$
κ_{OF}	10	Cost of deviating from capital requirements	Steady-state $\frac{K^b}{RWA^{OF}} = 9\%$
χ_{ν^b}	6.5	Sensitivity of capital requirements	Angelini, Neri and Panetta (2014)
ρ_{ν^b}	0.92	Persistence of capital requirements	Angelini, Neri and Panetta (2014)

Table 5: Prior and posterior distributions of the structural parameters

Parameter		Prior Distributions			Posterior Distributions			
		Type	Mean	Std dev.	Mean	2.5%	Median	97.5%
κ_{bH}	Mortgages rate adjustment cost	$\mathcal{G}$	6.00	2.50	6.89	3.70	6.68	10.43
κ_{bE}	NFC loans rate adjustment cost	$\mathcal{G}$	3.00	2.50	15.13	10.66	14.96	20.06
κ_d	Deposits rate adjustment cost	$\mathcal{G}$	10.00	2.50	4.87	2.62	4.66	7.59
κ_y	Degree of price stickiness	$\mathcal{G}$	100.00	20.00	93.09	60.93	91.86	128.35
κ_l	Degree of wage stickiness	$\mathcal{G}$	100.00	20.00	209.24	136.82	206.27	285.93
ι_y	Price indexation	$\mathcal{B}$	0.50	0.15	0.11	0.03	0.10	0.19
ι_l	Wage indexation	$\mathcal{B}$	0.20	0.15	0.03	0.00	0.02	0.09
κ_i	Investment adjustment cost	$\mathcal{G}$	50.00	5.00	47.03	37.69	46.92	56.60
ρ_R	Policy rate stickiness	$\mathcal{B}$	0.50	0.15	0.83	0.80	0.83	0.86
ϕ_π	Monetary policy response to π	$\mathcal{G}$	2.00	0.15	1.77	1.68	1.76	1.89
ϕ_Y	Monetary Policy response to y	$\mathcal{N}$	0.10	0.15	0.31	0.13	0.31	0.51
a^i	Habit coefficients	$\mathcal{B}$	0.70	0.20	0.96	0.93	0.96	0.97
		Shocks' Persistence						
ρ_A	TFP	$\mathcal{B}$	0.80	0.10	0.945	0.911	0.947	0.977
ρ_c	Consumption preference	$\mathcal{B}$	0.80	0.10	0.376	0.241	0.374	0.511
ρ_h	Housing preference	$\mathcal{B}$	0.80	0.10	0.890	0.832	0.892	0.943
ρ_{mH}	LTV on mortgages	$\mathcal{B}$	0.80	0.10	0.986	0.971	0.987	0.998
ρ_{mE}	LTV on loans to NFC	$\mathcal{B}$	0.80	0.10	0.987	0.975	0.988	0.998
ρ_{bH}	Mortgages mark-up	$\mathcal{B}$	0.80	0.10	0.877	0.802	0.878	0.948
ρ_{bE}	Loans to NFC mark-up	$\mathcal{B}$	0.80	0.10	0.799	0.603	0.812	0.972
ρ_d	Deposits mark-down	$\mathcal{B}$	0.80	0.10	0.786	0.696	0.793	0.861
ρ_{qk}	Investment efficiency	$\mathcal{B}$	0.80	0.10	0.181	0.1057	0.179	0.255
ρ_y	Price mark-up	$\mathcal{B}$	0.80	0.10	0.172	0.103	0.169	0.240
ρ_l	Wage mark-up	$\mathcal{B}$	0.80	0.10	0.517	0.393	0.519	0.638
ρ_{Kb}	Bank capital	$\mathcal{B}$	0.80	0.10	0.922	0.831	0.932	0.992
		Shocks' Standard Deviation						
σ_A	TFP	$\mathcal{IG}$	0.01	2.00	0.011	0.005	0.008	0.021
σ_c	Consumption preference	$\mathcal{IG}$	0.01	2.00	0.161	0.101	0.157	0.232
σ_h	Housing preference	$\mathcal{IG}$	0.01	0.05	0.208	0.091	0.201	0.330
σ_{mH}	LTV on mortgages	$\mathcal{IG}$	0.01	0.05	0.008	0.007	0.008	0.010
σ_{mE}	LTV on loans to NFC	$\mathcal{IG}$	0.01	0.05	0.008	0.007	0.008	0.010
σ_{bH}	Mortgages mark-up	$\mathcal{IG}$	0.01	2.00	0.673	0.433	0.642	1.003
σ_{bE}	Loans to NFC mark-up	$\mathcal{IG}$	0.01	2.00	0.297	0.002	0.332	0.474
σ_d	Deposits mark-down	$\mathcal{IG}$	0.01	2.00	0.169	0.111	0.162	0.243
σ_{qk}	Investment efficiency	$\mathcal{IG}$	0.01	2.00	0.031	0.027	0.030	0.035
σ_y	Price mark-up	$\mathcal{IG}$	0.01	2.00	4.352	2.865	4.291	6.067
σ_l	Wage mark-up	$\mathcal{IG}$	0.01	0.05	2.842	1.677	2.717	4.472
σ_{Kb}	Bank capital	$\mathcal{IG}$	0.01	0.05	0.034	0.020	0.033	0.052
σ_r	Monetary policy	$\mathcal{IG}$	0.01	0.05	0.003	0.002	0.003	0.003

Convergence test. While testing for convergence of the posterior distribution is notoriously difficult, Dynare uses some indicative statistics as recommended by Brooks and Gelman (1998)). Figure 8 contains three multivariate figures, representing convergence indicators for all parameters considered together. The multivariate diagnostics indicate that the chains converge to similar means and distributions, where interval refers to the interval measure, and m2, m3 refer to second and third order multivariate moment measures. As a minimum requirement, the multivariate diagnostics should be seen to converge to the same values. While, Figures 9, 10 and 11 show that prior and posterior distribution of the estimated parameters.

Figure 8: Convergence test

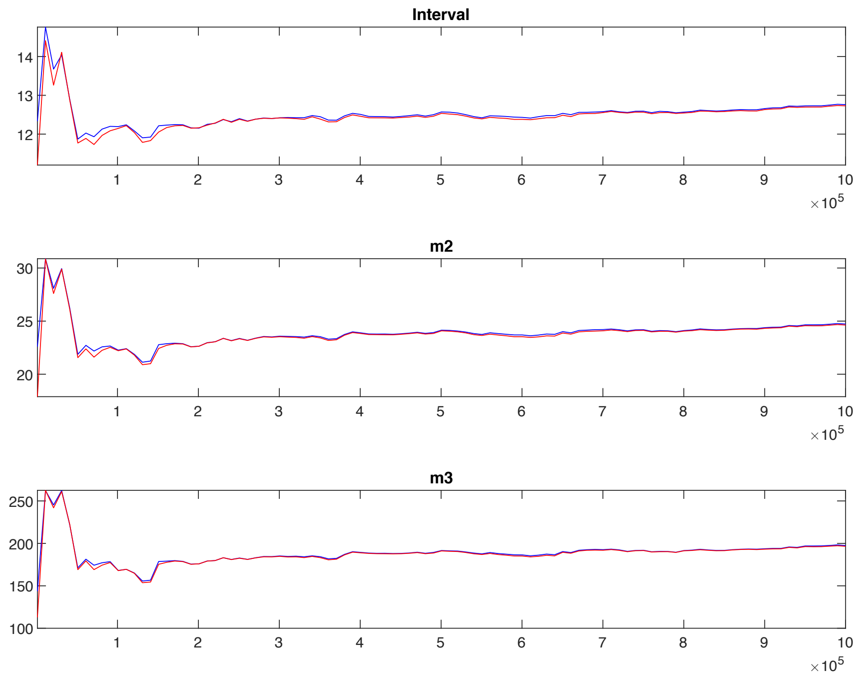


Figure 9: Prior and Posteriors: Standard deviations

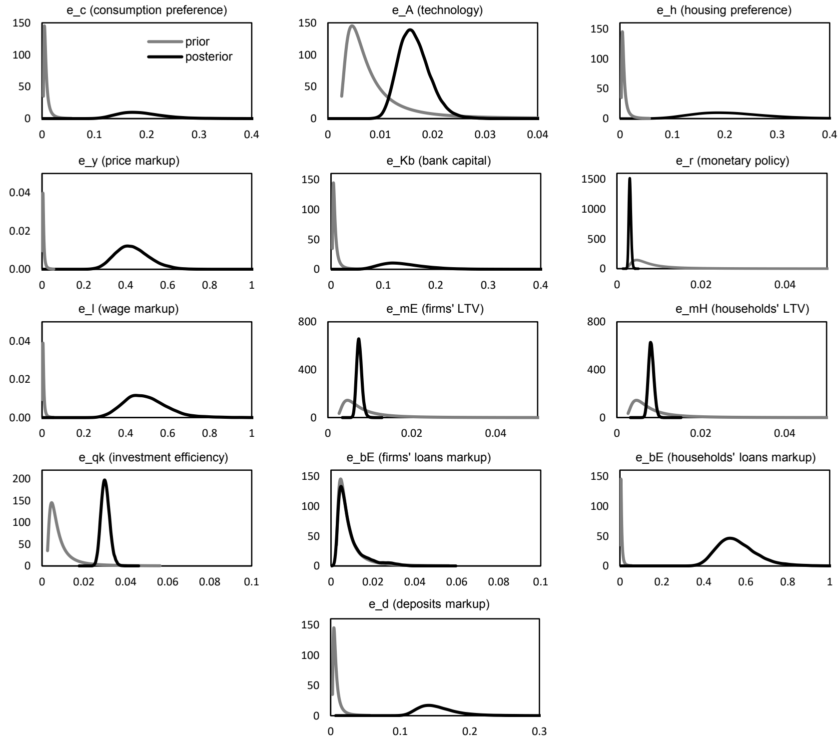


Figure 10: Prior and Posteriors: Shocks persistence

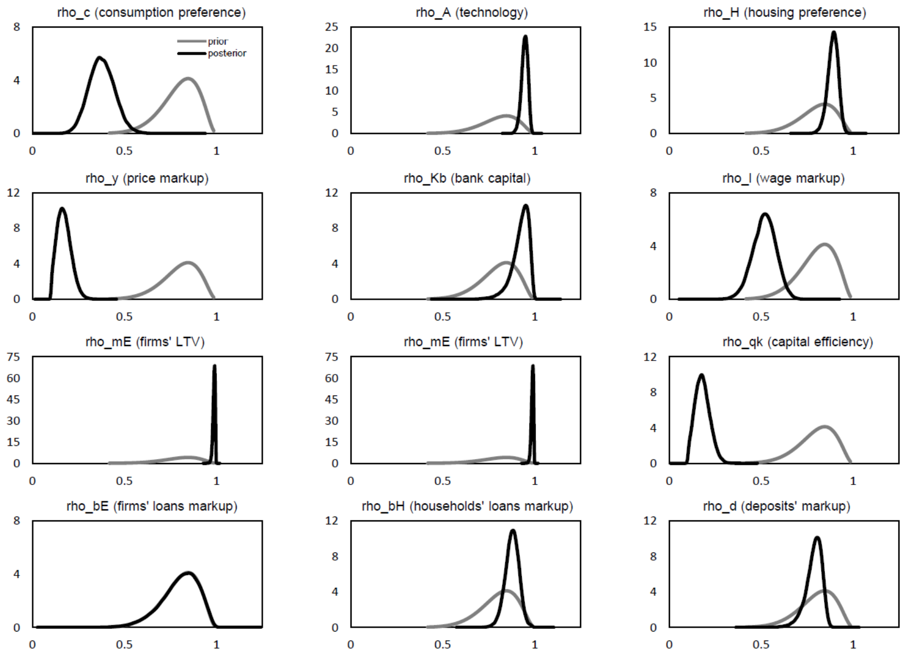
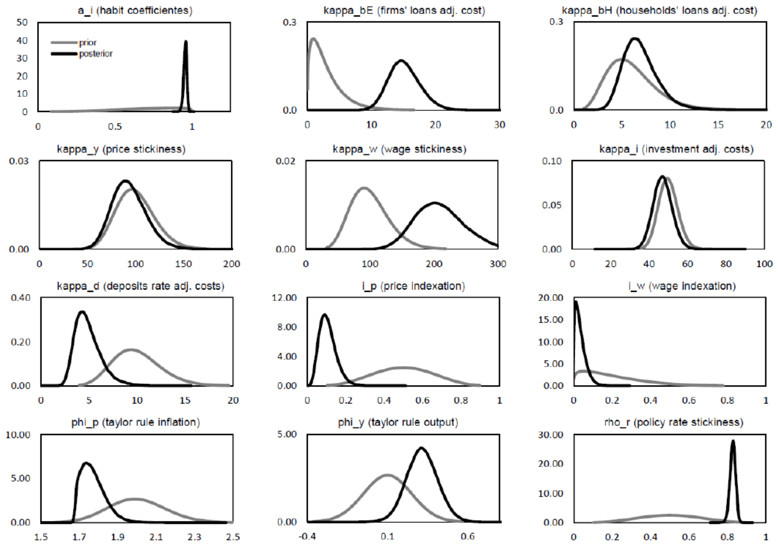


Figure 11: Prior and Posteriors: Structural parameters



D Appendix D. Additional results

Impulse response functions to a positive (TFP) shock. Figure 12, 13 and 14 show some additional relevant results for the TFP shock.

Figure 12: IRFs to a positive TFP shock

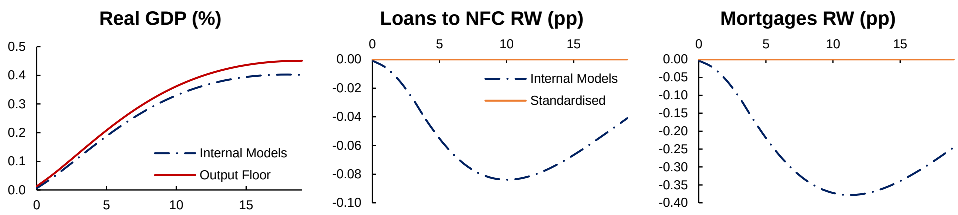


Figure 12 shows the responses to a positive technology shock of real GDP and risk weights. Modelled risk weights decline in response of the increase of the Real GDP. This generates downward pressures to the RWA.

Figure 13: Dynamics of the RWA after a positive TFP shock

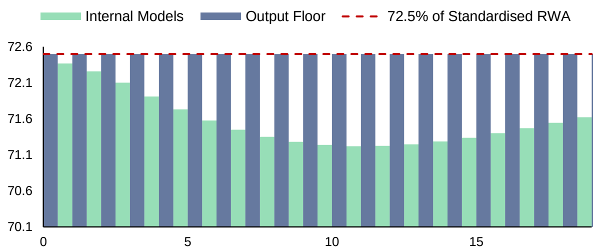


Figure 13 shows the dynamics of the RWA calculated with internal models and under the output floor, normalised with respect to the standardised RWA. The output floor is always binding.

Figure 14: IM-SA gaps after a positive TFP shock

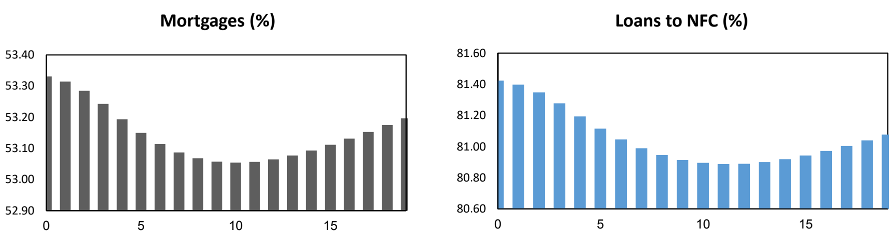


Figure 14 plots the gap between the modelled (IM) and the standardised (SA) risk weights - 100*$\left(\frac{w^{k,IM}}{w^{k,SA}}\right)$ – with $k \in \{H, E\}$ after the TFP shock. During the simulation period, the modelled risk-weight for mortgages is, on average, 53% of the standardised one, while the modelled risk-weight for loans to NFC is, on average, 81% of the standardised one.

Impulse response functions to a positive LTV shock. Figure 15 and 16 show some additional relevant results for the LTV shock.

Figure 15: IRFs to a positive LTV shock

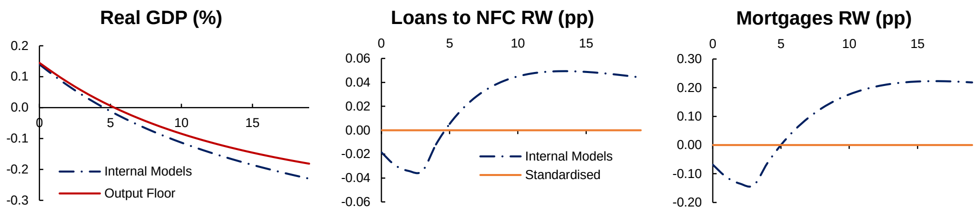


Figure 15 shows the responses to a positive LTV shock of real GDP and risk weights. Modelled risk weights initially decline in response of the increase of the real GDP, generating a reduction in the RWA. In these initial periods the output floor is binding. Around period 5, the response of the risk weights turns to be positive and the output floor to be slack.

Figure 16: Dynamics of the RWA after a positive LTV shock

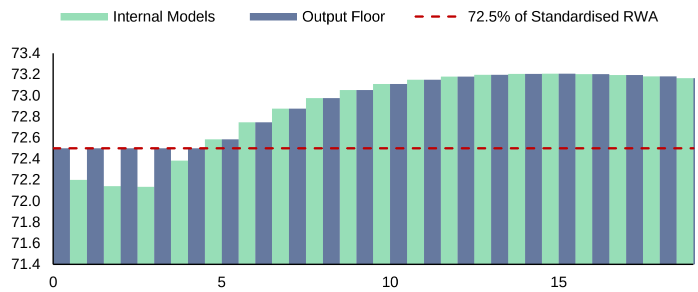


Figure 16 shows the dynamics of the RWA calculated with internal models and under the output floor, normalised with respect to the standardised RWA. The output floor is binding the first 4 periods after the shock.