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Abstract

We develop a two-sector DSGE model with a detailed banking sector along the lines of Clerc *et al* (2015) to assess the impact of macroprudential tools (minimum, countercyclical and sectoral capital requirements, as well as a loan-to-value limit) on key macroeconomic and financial variables. The banking sector features residential mortgages and corporate lending subject to staggered interest rates à la Calvo (1983), which is motivated by the sluggish movement of lending rates due to fixed interest rate loan contracts. Other distortions in the model include limited liability, bankruptcy costs and penalty costs for deviations from regulatory capital. We estimate the model using Bayesian methods based on quarterly UK data over 1998 Q1–2016 Q2. Our contributions are threefold. We show that: (i) co-ordination of macroprudential tools may have a welfare-improving effect, (ii) macroprudential tools would have improved some macroeconomic indicators but, within our model, not have prevented the Global Financial Crisis, (iii) staggered interest rates may alter the transmission of macroprudential tools that work through interest rates.

Key words: Sectoral DSGE model, macroprudential policy, interest rate stickiness.

JEL classification: E32, E58, G18, G21.

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1 Introduction

In the aftermath of the Great Recession, many regulators around the world added policy instruments to their toolkit designed to moderate the effects of future financial crises on the real economy (for an overview, see BCBS, 2019). In the United Kingdom this included the creation of a Financial Policy Committee (FPC), with powers to set a range of macroprudential policies. The policies include capital tools, such as the ability to set a countercyclical capital buffer (CCyB) for the U.K. on top of banks' minimum (static) capital requirements and higher sectoral capital requirements (SCRs) on residential and commercial property as well as intra-financial exposures. The FPC also has powers over loan-to-value (LTV) and debt-to-income (DTI) limits for owner-occupier mortgages, and LTV and interest coverage ratio limits for buy-to-let mortgages, secured on properties in the U.K.[1]

We seek to answer several questions in this paper regarding the U.K. macroprudential framework's effects and effectiveness: what is the impact the different tools have on the economy and welfare? How do the different macroprudential tools interact with each other? What are the main channels of transmission through which these policies operate? Are regulators better equipped to face the next financial crisis? A better understanding of these issues can help regulators to fine-tune their toolkit, understand how best to deploy their policies, and assess any unintended consequences. In particular, knowledge of how the different tools may interact with each other when used in combination is currently limited. Assessing the interactions and coherence among different policies is also part of the Basel Committee's work programme for evaluating and monitoring the impact of post-crisis reforms.[2]

To provide insight on these questions we build a dynamic stochastic general equilibrium (DSGE) model based on Clerc et al. (2015), featuring a detailed banking sector, various financial frictions and a macroprudential toolkit. The model comprises of both a housing and corporate sector. Prudential policies include minimum capital requirements, which can vary by sector (akin to an SCR), the CCyB, and the LTV limit for households. We estimate the model using Bayesian methods based on quarterly U.K. data from 1998Q1 to 2016Q2.

The model by Clerc et al. (2015) provides a natural starting point for our analysis as it represents a comprehensive framework for assessing the effectiveness of banking regulations, especially capital requirements. The model is one of the first of its kind to introduce defaults not only at the level of the borrower but also at the bank level. The model provides a clear rationale for capital regulation, which trades off the higher costs of scarce capital with the benefit of improving banking

[1] For a complete list of the FPC's powers, see www.bankofengland.co.uk/financial-stability.

[2] See www.bis.org/bcbs/bcbs_work.htm, accessed 14 February 2020.

system resilience. At the same time, the model serves as an appropriate framework to study macroprudential interactions, because it captures the essential trade-off associated with the LTV limit. This feature allows us to perform a detailed welfare analysis, to evaluate the effect of policy interactions, and to analyse jointly optimal macroprudential policy tools.

We deviate from Clerc et al. (2015) by adding three features to the model: (i) interest rate stickiness as in Calvo (1983), (ii) LTV limit as a macroprudential tool, and (iii) penalty costs for deviations from minimum capital requirements. The details of each of these features are explained in the model section.

We pay particular attention to modelling the role of interest rates in the transmission mechanism of macroprudential policies through the introduction of interest rate stickiness. Interest rates likely play a crucial role in determining the impact of policy interventions. For example, the implications of an increase in capital requirements will depend on the extent to which banks pass on the increase in funding costs to interest rates faced by borrowers.[3] Most academic papers in the DSGE literature assume (at least implicitly) that interest rates adjust instantaneously, i.e. interest rates are not subject to any frictions.[4] In contrast, the idea of price stickiness in the goods market is a key aspect of and widely implemented in New Keynesian models.

Following Kobayashi (2008) and others, interest rate stickiness could arise for two different reasons. First, there may be adjustment costs with respect to making changes to loan rates. This may be due to customers' costs of changing banks (switching costs), menu costs of changing interest rates, or a highly regulated or less competitive banking sector. Second, the presence of overlapping multi-period loan contracts with fixed interest rates (for the whole or at least some of the duration of the mortgage contract) could prevent, in the aggregate, an instantaneous adjustment of interest rates in response to policy actions.

We model interest rate stickiness by adapting Calvo's (1983) framework for price adjustments to the setting of interest rates for loan contracts. Our preferred interpretation is that, following the second rationale above, many loan contracts in the U.K. are subject to a specified initial period during which interest rates do not change, usually between two to five years in the case of residential mortgages. After the end of this period, the mortgages revert to a floating rate, unless the respective borrower is able to remortgage.[5] As a consequence, the effective interest rate, i.e. the average interest rate on all of a bank's outstanding loan contracts, does not change instantaneously in response to factors

[3]Of course, these costs need to be weighed against the benefits of higher capital requirements, i.e. a reduction in the probability and severity of financial crises.

[4]Some notable exceptions include Gerali et al. (2010) and Darracq-Paries et al. (2011).

[5]We therefore refer to interest rate stickiness in this paper also as staggered interest rates, but use the terms interchangeably.

that affect the level of interest rates, such as external shocks or monetary and macroprudential policies.

Our contributions to the literature are threefold. First, we find that the coordination (i.e. joint optimisation) of macroprudential tools may have a welfare-improving effect, compared to optimising each tool in isolation. Second, we perform a counterfactual exercise with the optimal policy settings. Our analysis indicates that macroprudential tools would have improved some macroeconomic indicators but, within our model, they would not have been able to prevent the Global Financial Crisis. Third, our results suggest that interest rate stickiness plays an important role for the transmission of shocks through the economy and for the effectiveness of macroprudential tools that work through interest rates.

The paper is organised as follows. The remainder of Section 1 reviews the existing literature and provides an econometric rationale for staggered interest rate contracts in the U.K. Section 2 describes the model, while Section 3 sets out the estimation methodology. In Section 4, we analyse the effects of macroprudential policy tools on household welfare and other economic variables. Section 5 discusses the effects of individual shocks on key variables through impulse response functions, with a particular focus on the role of interest rate stickiness. Section 6 concludes.

1.1 Literature review

The literature on the role of banks in DSGE models and financial frictions has been growing rapidly since the financial crisis of 2008. Our model attempts to bring together two streams of the literature. One is based on the seminal paper by Bernanke, Gilchrist and Gertler (1999, subsequently referred to as BGG), where some fraction of borrowers default in equilibrium. Borrowers default due to limited liability and shocks (both aggregate and idiosyncratic) which cause the value of the asset to fall below the loan amount. The other stream of literature is based on borrowing constraints as in Kiyotaki & Moore (1997).

Several papers have built on the BGG framework to include a role for the banking sector. As in BGG, most papers assume that the return on debt is state contingent, implying that banks or financial intermediaries make a risk free return. Thus, in these models, there is no role for bank capital. Clerc et al. (2015) depart from this assumption, and develop a model where banks are exposed to risk and can default in equilibrium. Banks are also prone to taking higher risk due to limited liability and deposit insurance. Their model features a meaningful trade-off between the cost of banking sector defaults on the one hand and higher cost of capital on the other. This enables a normative as well as positive analysis of bank capital requirements.

Our main extensions compared with Clerc et al. (2015) are the introduction of staggered interest rate contracts, an LTV limit, SCRs and a penalty cost function for deviations from regulatory capital requirements. This set-up allows us to analyse the interaction between capital instruments and borrowing constraints. Mendicino et al. (2018) build upon their model by analysing optimal dynamic capital requirements under a rich stochastic structure, calibrated to EU data. The model highlights trade-offs associated with capital requirement in terms of welfare gains of borrowers as compared to savers in the economy. The model in Mendicino et al. (2020) compares the long-term benefits against short-run transition costs associated with capital requirements. Capital requirements make the banking system safer in the long run whereas transition costs amount to 25% of the long-term welfare gains. Benes & Kumhof (2011) also develop a model that features both borrower and bank level default. They study the role of a countercyclical capital policy in a monetary economy and find significant welfare gains. Hodbod et al. (2018) develop a similar model and show how a countercyclical risk weight can be used as a macroprudential tool to attenuate the financial cycle. Lozej et al. (2018) evaluate different rules for setting countercyclical buffers in a small open economy model for the Irish economy.

The other stream of literature on financial frictions pertains to models with borrowing constraints in the form of a collateral constraint as in Kiyotaki & Moore (1997). Iacoviello (2005) builds a DSGE model with a housing sector and collateral constraints to analyse the transmission of monetary policy. Mendoza & Bianchi (2011) and Jeanne & Korinek (2010) provide a rationale for macroprudential policies due to a pecuniary externality associated with collateral constraints. Gerali et al. (2010) explore the role of banking sector related shocks in a model with binding collateral constraints.

In this paper, we bring together these elements, so that borrowers (and banks) can strategically default and borrowers are subject to a collateral constraint on new loans (which appears in the model as an LTV limit). The advantage of this approach is that the collateral constraint can be looked upon as a LTV limit imposed by the bank as well as a policy instrument of the regulator. Another paper that attempts to do so is Nookhwun & Tsomocos (2017). They attempt to explain the financial crisis with a default risk shock and a risk premium shock in a DSGE model, similar to Clerc et al. (2015). They analyse the role of macroprudential policy tools such as countercyclical capital buffers, an LTV limit and state contingent LTV limit.[6]

[6]Other recent papers with a key role for a banking sector within a DSGE framework include Goodfriend & McCallum (2007), Curdia & Woodford (2010), Bianchi (2011), Meh & Moran (2010), Forlati & Lambertini (2011), Christiano et al. (2014) and Karmakar (2016).

While macroprudential and monetary policy interactions have received attention in the recent literature[7], few papers look at the interaction of different prudential policies in the same model. For example, Boissay & Collard (2016) study the transmission mechanism of liquidity and capital regulations in a DSGE model. They find that both policies reinforce each other and support Basel III's "multiple metrics" approach. Goodhart et al. (2013) study multiple financial regulations in an integrated framework using a simplified model. They analyse combinations of capital regulations, margin requirements, liquidity regulation, and dynamic provisioning to achieve financial stability and maximise welfare. Popoyan et al. (2017) develop an agent-based model to study the macroeconomic impact of macroprudential regulations and their possible interactions with alternative monetary policy rules. Ingholt (2019) considers the interaction between multiple occasionally binding constraints in the form of LTV and DTI limits. Aikman et al. (2019a) provide an empirical assessment of whether prudential tools would have been effective in the build-up to the financial crisis. In terms of interest rate stickiness, to our knowledge, Gerali et al. (2010) and Darracq-Paries et al. (2011) are the only other papers to model sticky interest rates in a DSGE framework in a similar fashion. Ferrero et al. (2018) present a model featuring an LTV ratio along with nominal rigidities to jointly study the optimal LTV limit and monetary policy. Their results suggest a role for LTV limits, which are countercyclical as they enhance risk sharing, attenuate debt-deleveraging and avoid a liquidity trap. Lindé et al. (2020) develop a model featuring long-term debt, housing transaction costs and a zero lower bound and focus on borrower-based macroprudential tools (LTV and LTI limits) both in the long and short run. Their results suggest that although long-term costs of both the macroprudential tools are moderate, the LTV ratio could be twice as costly in terms of consumption compared to the LTI policy in the short run at the zero lower bound.

We explore one of the sources of interest rate stickiness related to the nature of the loan contract, i.e. fixed interest rate loans, in the empirical section of this paper.[8] Fixed-rate contracts and longer-term loan contracts are not often reflected in macroeconomic models, with some notable exceptions, such as Bluwstein et al. (2018) and Greenwald (2018). However, there is a broader empirical strand of the literature from the 90s that assesses how interest rates adjust. For example, some studies examine the presence of a highly regulated or less-competitive financial sector (Hannan & Berger, 1991, Neumark & Sharpe, 1992), adjustment/menu costs in changing loan rates (Mester & Saunders, 1995), and customers' costs of changing banks (Neumark & Sharpe, 1992). Lowe & Rohling (1992) provide theory and evidence on interest rate stickiness. They consider theories that are based on equilibrium credit rationing, switching costs, implicit risk sharing and consumer

[7]Some examples include Quint & Rabanal (2013), Collard et al. (2017), Gelain & Ilbas (2017) and Aikman et al. (2019b).

[8]For the sake of clarity, the interest rate stickiness in this paper is with respect to lending rates and not with respect to monetary policy rates or Taylor rule inertia.

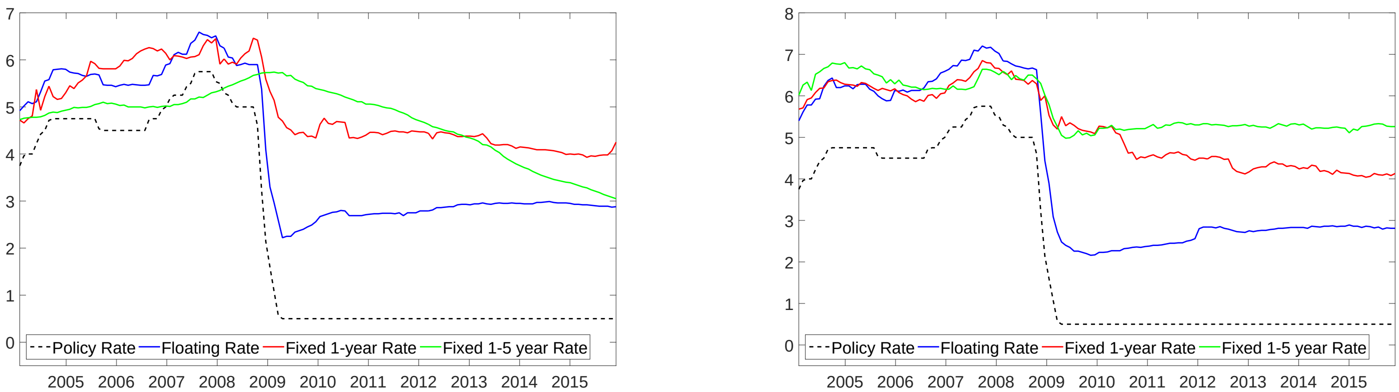
irrationality. Their empirical evidence provides support for the switching cost explanation. More recently, Driscoll & Judson (2013) examine the dynamics of eleven different deposit rates for a panel of over 2,500 branches of about 900 depository institutions observed weekly over ten years. They find that rates are downwards-flexible and upwards-sticky, and show that a simple menu cost model can generate this behaviour. Berstein & Fuentes (2003) provide evidence that the lending rates in Chile are flexible as compared to most other countries. Moazzami (1999) finds that lending rates in the US have been stickier than those in Canada. However, the US lending rate rigidity has decreased in recent years. Sørensen & Werner (2006) investigate the pass-through between market interest rates and bank interest rates in the euro area. They find heterogeneity in interest rate pass-through across loan products and that the speed of adjustment of interest rates is slow. Nakajima et al. (2009) show that the loan rates are sticky with respect to the policy interest rate in all Eurozone countries for all loan maturities, the degree of stickiness differs across the countries, and the degree of difference is more prominent for longer loan maturities. Andries & Billon (2016) provide a survey of the empirical literature on interest rate pass-through. The results show that although there is complete long-run pass-through of interest rates, there is incomplete short-run pass-through and a heterogeneous adjustment of bank interest rates across bank products and Eurozone countries.

1.2 Interest Rate Stickiness in the U.K.

Although interest rate stickiness could arise due to a number of reasons described in the literature, such as market power, level of competition, regulation, switching/menu costs etc., we highlight the importance of interest rate stickiness emanating from the nature of loan contracts, i.e. the existence of long-term and fixed interest rate loans. The effective interest rate of a given portfolio of loans is based on a mix of older loans (repaid over time) that pay an interest rate fixed in the past, and newer loans that pay interest at the current market rates. As a result, even if market interest rates change, the effective interest rates would not fully adjust immediately. They change slowly as the older loans are repaid and new loans are added to the loan portfolio over time.

In this section, we provide some graphical and econometric insight into the behaviour of effective lending rates for different terms of interest rate fixation. Figure 1 shows monthly data on effective interest rates between January 2004 and January 2016 for mortgage and business loans in the U.K. for different terms of interest rate fixation from the Bank of England's statistics website.

As can be seen, the response of variable interest rate loans when the policy rate changes is faster than the response of fixed interest rate loans. In general, the response of fixed interest mortgages decreases the longer the initial fixed portion of the loan contract.



(a) Effective mortgage lending rates

(b) Effective corporate lending rates

Figure 1. Effective monthly lending rates in the U.K. from 2004 to 2016. The x-axis shows the dates, and the y-axis shows the lending rates in percentages.

Interest rate stickiness can vary across different sectors, depending on the proportion of long term contracts in the portfolio. Based on a visual inspection of Figure 1, interest rate pass-through appears slower for the mortgage loan portfolio, compared to the business loan portfolio, especially for the 1 to 5 year fixed rates. We perform a more rigorous econometric analysis in the next section.

1.2.1 Econometric Methodology

We assess econometrically how lending rates adjust in response to a change in the central bank policy rate. Following the empirical literature on interest rate pass-through, we run a vector error correction model, where policy interest rates are considered to be the most direct determinants of retail bank lending rates. We run the following vector error correction model based on Johansen (1991):

$$\Delta R_t = \sum_{k=1}^{K} \delta_k \Delta R^m_{t-k} + \sum_{q=0}^{Q} \gamma_q \Delta i_{t-q} + \alpha(\mu + R^m_t - \beta i_t) + u_t \tag{1.1}$$

where R_t is the effective lending rate, i_t is the Bank of England policy interest rate, the coefficient β is the long-run equilibrium relationship between the bank lending rate and policy rate, and the coefficient α is the speed of adjustment of the lending rate to the long-run equilibrium. The coefficients of the lags of the first difference of the policy rate capture the short-run response of lending rates to the policy rate. We conduct this exercise for three different lending rates in the mortgage sector: a variable interest rate, a fixed interest rate for a term of up to 1 year, and a fixed interest rate for a term of 1 to 5 years. The results are summarised in Table 1.[9]

Regressor	Floating rate	Fixed < 1 year	Fixed 1 to 5 year
γ_0	0.016***	0.0057	0.0025
γ_1	0.896***	0.435***	0.018
γ_2	0.016	-0.293***	-0.0158
γ_3	-0.008	0.242***	0.0097
γ_4	-0.196***	-0.037	0.0054
constant	0.1366***	-	-

Table 1. Regression of U.K. mortgage rates on BoE policy rate.

The results in Table 1 suggest that floating interest rates adjust faster than fixed-term interest rates, where the coefficients $\{\gamma_j\}_{j=0}^4$ capture the response of interest rates to the central bank policy rate. In the case of floating interest rate loans, the response on impact is low. However, around 90 percent of the pass-through takes place in the following month. The response of floating interest rates is higher than the response of 1 year fixed rate loans, which in turn is higher than the response of the 1 to 5 year fixed rate loans. In case of fixed term loans of up to 1 year, the response on impact is less than 0.01 percentage points, and around 45 per cent of the pass-through takes place in the following month.

For the fixed rate loans, the sum of short-run coefficients is less than unity, suggesting an incomplete pass-through of the policy interest rate. Accordingly, the pass-through to the fixed interest loans is not only sluggish but also incomplete, whereas the pass-through to floating interest rate loans is faster and almost complete. However, in all cases with floating interest rate, the response of the lending rate on impact is low (less than 2 percent). The faster rate of adjustment for floating interest rates, compared to fixed-term interest rates, implies that fixed-rate contracts are an important source of interest rate stickiness. Appendix C provides additional cross-country evidence on interest rate stickiness.

2 Model Summary

Our model closely follows Clerc et al. (2015), which augments the baseline model of Bernanke et al. (1999) with a detailed banking sector and two different types of households, corporates and banks to determine the optimal capital adequacy ratio (CAR) for the banking sector, as well as to analyse

[9] *** is 1 per cent, ** is 5 per cent and * is 10 per cent level of significance.

the macroeconomic implications of bank capital structure under different shocks.

The BGG framework assumes that interest rates charged by banks are state contingent. Hence, higher interest rates charged on non-defaulters are sufficient to meet the losses arising from defaulters. This means that banks always make a risk-free return on their investments, which makes the capital structure of the bank irrelevant in the original BGG framework. Clerc et al. (2015) depart from the BGG framework by assuming a non-contingent lending rate, which implies that banks may suffer losses in the event of defaults by borrowers. Therefore, with costly state verification of borrowers, defaults are costly and entail a dead-weight loss for the economy, which necessitates a role for bank capital. They further assume that investor wealth is scarce and hence the cost of equity capital is higher than debt funding. Therefore, while bank capital is necessary to avoid higher default rates, it is also expensive at the same time, thus creating a trade-off for holding capital.

We differ from the Clerc et al. (2015) by adding the following three features to the model:

Interest rate stickiness

On the banking side, we introduce staggered interest to capture the stickiness of mortgage and corporate lending rates, which is motivated by the empirical evidence shown in Section 1.2. We incorporate interest rate stickiness to the model by assuming that only a fixed proportion of banks are allowed to change their interest rates as in Calvo (1983).

LTV limit

A key feature of the mortgage lending market is the presence of a loan-to-value (LTV) limit. We assume that the LTV limit is set by the regulator. The LTV limit is similar to an exogenous collateral constraint as in Iacoviello (2005). Our focus in this paper is on the household LTV limit, since the Financial Policy Committee (FPC) in the U.K. does not have such a regulatory tool on corporate lending.

Penalty costs

We endogenise the bank's capital level by allowing it to be determined in equilibrium through the bank's decision problem. Accordingly, the bank maximises over its lending rates to households and businesses subject to interest rate stickiness. We introduce penalty costs for deviation from the minimum capital requirement, so as to create an incentive (precautionary motive) for banks to have a capital adequacy ratio higher than the minimum prescribed. This is a realistic setup since banks typically maintain voluntary capital buffers to ensure they do not breach the regulatory minimum. This differs from Clerc et al. (2015), which assumes that banks always hold the minimum capital requirement.

Other key distortions and frictions in the model closely follow Clerc et al. (2015), i.e. both the bank and borrowers (mortgage or corporate) in the model are subject to limited liability. The limited liability of banks and the presence of a deposit insurance agency implies that banks have an incentive to over-lend, since they do not fully internalise the costs of default. The bank also has an incentive to over-borrow since deposit financing is cheaper than equity financing. In this framework, regulatory capital is a means to restrict the use of excessive bank leverage. The model further features costly state verification, which implies that the use of leverage is more expensive and that defaults are costly.

The key agents in the economy are patient and impatient households, entrepreneurs, a bank that lends in the corporate and mortgage sectors, a deposit insurance agency, and housing, capital and final goods producers. Figure 2 provides an overview of the main interactions between these agents along with the regulatory tools present in the model. Below we summarise the maximisation problems for each agent type, while the associated first-order conditions and further details can be found in Appendix D.

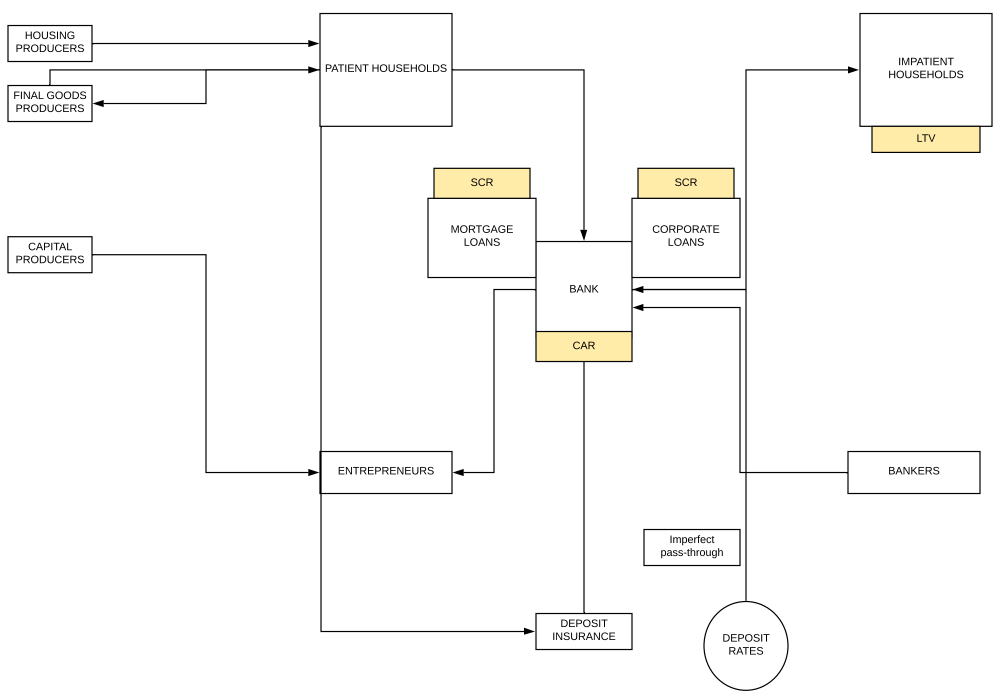


Figure 2. Overview of the main actors and regulatory tools in the model.

2.1 Overview of Agents

Households: there are two types of households, patient and impatient, with patient households having a higher discount factor, as in Iacoviello (2015). Both patient and impatient households have concave utility functions and derive utility from consumption goods, housing and leisure. The individual households are a part of a representative dynasty, which provides perfect risk sharing within the group. Thus, all individual households within the type are ex-ante identical. While the individuals face idiosyncratic shocks, they are perfectly insured within their dynasty and hence consume and save/borrow identically. Both households supply labor in a competitive labor market.

Patient households are savers who supply deposits to the bank in equilibrium, and buy houses with their own funds. Both household types derive utility from consumption as well as housing goods, and dis-utility from labor. As such, the patient household's maximisation problem is given as:

$$\max_{c_t^s, L_t^s, D_t, H_t^s} E_t \sum_{t=0}^{\infty} \beta_s^t [E_{C,t} log(\hat{c_t^s}) + vlog(H_t^s) - \frac{E_{H,t}(L_t^s)^{1+\eta}}{1+\eta}], \tag{2.1}$$

subject to the following budget constraint:

$$c_t^s + q_t^H H_t^s + D_t = w_t L_t^s + q_t^H H_{t-1}^s (1-\delta) + D_{t-1} R_t^D + \pi_t, \tag{2.2}$$

where $\hat{c_t^s} = c_t^s - \lambda c_{t-1}^s$, i.e. consumption is subject to habit formation with parameter λ. π_t includes profits of final goods producing firms and investment and housing production firms (which are owned by patient households), dividends from entrepreneurs and lump-sum transfers from the deposit insurance agency. The households are subject to preference shocks on housing and consumption $E_{J,t}$ and $E_{C,t}$, which affect their taste for housing and consumption goods, respectively. These shocks can be equivalently interpreted as the degree of risk aversion to spending on housing and consumption goods.

Impatient households borrow from banks using their houses as collateral. Mortgage loans are made on a limited-liability basis, which implies that individual households can default whenever the value of their house is lower than the outstanding mortgage loans. The value of the house depends both on aggregate shocks, which affect the value of their house, as well as idiosyncratic shocks which affect the default decision of individual borrowers. In equilibrium, borrowers with an idiosyncratic shock below a certain threshold default, in which case the bank takes possession of the house subject to a state verification cost.

With the exception of having a different discount factor, the impatient household is subject to the same preference shocks and has the same objective function as the patient household, which is given as follows:

$$\max_{c_t^m, B_t^m, L_t, H_t^m} E_t \sum_{t=0}^{\infty} \beta_m^t [E_{C,t} log(\hat{c_t^m}) + \upsilon E_{H,t} log(H_t^m) - \frac{(L_t^m)^{1+\eta}}{1+\eta}], \tag{2.3}$$

with $\hat{c_t^m} = c_t^m - \lambda c_{t-1}^m$ similar to patient households, subject to the following budget constraint reflecting their borrowings under limited liability:

$$c_t^m + q_t^H H_t^m - B_t^m = w_t L_t^m + \int_{\bar{\omega_t^m}}^{\infty} \left(\omega_t^m q_t^H H_{t-1}^m (1-\delta) B_{t-1}^m R_{t-1}\right) \, dF\omega_t^m + P_t. \tag{2.4}$$

The term under the integral reflects the limited liability of the borrowers as they default on their loans when the idiosyncratic shock ω_t^m is below the threshold level of $\bar{\omega^m}_t$. The default threshold of the borrowers is determined by:

$$\bar{\omega_t^m} q_t^H H_{t-1}^m (1-\delta) = B_{t-1}^m R_{t-1}^m, \tag{2.5}$$

We introduce a loan-to-value (LTV) limit set by the macroprudential regulator on the flow of new lending, which is similar to a collateral constraint as in Kiyotaki & Moore (1997). The LTV limit (or the borrowing constraint) is given by:

$$[B_t^m - (1-rp)B_{t-1}^m] R_t \leq E_{LTV,t} \epsilon_t^m E_t [q_{t+1}^H [H_t^m - H_{t-1}^m (1-\delta)]], \tag{2.6}$$

where rp denotes the loan repayment rate and ϵ_t^m is the LTV limit. The constraint is always binding at the equilibrium,[10] and we introduce a shock on the limit, $E_{LTVH,t}$, in order to relax the restrictiveness of this constraint.

Entrepreneurs are risk neutral agents who own and maintain the stock of physical capital. They rent capital to the final goods producing firms. Entrepreneurs derive utility from transferring part of their wealth to the saving dynasty by paying out dividends and retaining the rest for the next period as retained earnings. Entrepreneurs invest in capital goods and finance their investment by means of their own funds, i.e. net worth, and borrowings from banks. Similar to mortgage loans, these are limited liability loans and hence subject to default by individual entrepreneurs in the event of the value of assets falling below the value of outstanding loans. The value of the capital depends both on aggregate shocks as well as idiosyncratic shocks, which affect the default decision. In equilibrium, entrepreneurs with an idiosyncratic shock below a certain threshold default. As in

[10] The corresponding Lagrange multiplier for impatient households is positive, which implies that the LTV limit is always binding.

the case of households, assets are seized by banks and subject to costly state verification costs. The entrepreneurs' decision rule is given as follows:

$$\max_{K_t, B_t^e} E_t(W_{t+1}^e), \tag{2.7}$$

with

$$W_{t+1}^e = max[\omega_{t+1}^e(r_{t+1}^k + (1-\delta)q_{t+1}^K K_t) - R_t^F b_t^e, 0]. \tag{2.8}$$

The default decision of the entrepreneurs is determined by:

$$\bar{\omega^e}_t q_t^K K_{t-1}^m (1-\delta) = B_{t-1}^e R_{t-1}^f. \tag{2.9}$$

The entrepreneurs are subject to a borrowing constraint on the flow of net borrowing, similar to the impatient households:

$$[B_t^e - B_{t-1}^e(1-rp)]R_t^f \leq \epsilon_t^e E_t[q_{t+1}^F[K_t - K_{t-1}(1-\delta)]], \tag{2.10}$$

which is always binding at the equilibrium, similar to the LTV limit for households. It is important to distinguish the policy parameter ϵ_t^m on the household LTV limit in (2.6), and the borrowing constraint parameter ϵ_t^e in (2.10): the former is a macroprudential policy tool, whereas the latter is only a parameter that reflects the borrowing constraint for the entrepreneurs.

A fixed proportion of wealth χ^e is paid out as dividends. This simple dividend paying rule for the entrepreneurs is given by:

$$c_t^e = \chi^e W_t^e E_{We,t}, \tag{2.11}$$

where $E_{We,t}$ denotes a net worth shock, which is a transfer from the patient households to the businesses, and can be thought of as a proxy for an exogenous government spending shock in our model.[11]

As a result, the retained earnings by the entrepreneurs are given by:

$$n_t^e = (1-\chi^e)W_t^e E_{We,t}. \tag{2.12}$$

The balance sheet identity of the entrepreneurs follows as:

$$n_t^e + B_t^e = q_t^K K_t. \tag{2.13}$$

[11]This shock affects the budget constraint of patient households through the profit term π_t.

Banks are financial intermediaries who channel savings from the savers to the borrowers. On the asset side of the banks, there are loans to households (mortgage lending) and entrepreneurs (business lending) respectively. As described earlier, these loans may default depending on aggregate state shocks and idiosyncratic borrower shocks in which case the banks seize the assets subject to state verification costs, which can also be viewed as bankruptcy costs.

On the liability side of the banks, there are deposits held by the patient households and equity capital held by the bankers. Deposits are insured by the Deposit Insurance Agency (DIA). There is a capital adequacy requirement set by the regulator which, along with a penalty cost function, determines the amount of equity capital held by the bankers.

One of the key features of the model is that banks may also default depending on the performance of their loan portfolios, which is driven by an aggregate shock and idiosyncratic shocks similar to the impatient households and entrepreneurs. The banks face an idiosyncratic shock to their returns on loans and therefore, in equilibrium, a fraction of banks below a certain threshold of the idiosyncratic shock level defaults. In case of default, the bank loan assets are possessed by the DIA, subject to costly state verification.

The banks' balance sheet identity is as follows:

$$E_{CAB,t}n_t^b + D_t = B_t^m + B_t^e, \tag{2.14}$$

where $E_{CAB,t}$ denotes a bank capital shock that affects its capital ratio. Their optimisation problem is given by:

$$\max_{R_t^{mi},R_t^{fi}} E_t \sum_{t=0}^{\infty} \xi^t \beta_s^t [\{(1-G_{t+1}^H)(\widetilde{R_t^{mi}})(B_t^{mi}) + (1-G_{t+1}^F)\widetilde{R_t^{fi}} B_t^{ei}\} - (1-F_{t+1}^b)R_t^D D_t + PC_t], \tag{2.15}$$

with PC_t the penalty cost for violating the regulatory requirements as will be described below, and:

$$\widetilde{R_t^{mi}} = E_{markup^m,t}(1-E_tF_{t+1}^m)R_t^{mi} + E_tG_{t+1}^m(1-\mu^m)(R_t^{mi}/E_t\bar{\omega}_{t+1}^m), \tag{2.16}$$

$$\widetilde{R_t^{fi}} = E_{markup^F,t}(1-E_tF_{t+1}^e)R_t^{fi} + E_tG_{t+1}^e(1-\mu^e)(R_t^{fi}/E_t\bar{\omega}_{t+1}^e), \tag{2.17}$$

where $E_{markup^m,t}$ and $E_{markup^F,t}$ denote two mark-up shocks on the interest rate setting, which affect the cost of mortgage and corporate lending respectively. These mark-up or cost-push shocks help introduce a wedge between the realised interest rates and the rates that the bank would use in the absence of interest rate stickiness. The demand for loans is given by:

$$B_t^{mi} = (\frac{R_t^{mi}}{R_t^m})^{-\tau} B_t^m, \tag{2.18}$$

$$B_t^{ei} = (\frac{R_t^{fi}}{R_t^f})^{-\tau} B_t^e. \tag{2.19}$$

Penalty costs for violating the regulatory requirements are modeled as a non-pecuniary gain in utility if the capital adequacy ratio is higher than the minimum capital requirement and a non-pecuniary cost if the capital adequacy ratio is lower than the minimum capital requirement with the following functional form:

$$PC_t = \nu^b \frac{[\frac{\phi_t^b}{\varphi_t}]^{1-\sigma} - 1}{1-\sigma}, \tag{2.20}$$

with ϕ_b the bank's capital ratio, and φ_t the minimum capital requirement as will be explained below. The functional form for the penalty function is based on Nookhwun & Tsomocos (2017). The marginal gains of having excess capital are decreasing, whereas the marginal costs of having a shortfall in capital are increasing, whenever σ is greater than 1. This creates an incentive for banks to maintain capital at a higher level than the minimum regulatory requirement. In reality, we find that banks do maintain capital buffer over what is the minimum required, see e.g. Nier & Baumann (2006). The parameter ν^b determines the weight attached to these penalty costs.

Staggered interest rates: while we find that one of the main sources of interest rate stickiness is the existence of fixed interest rate loans as shown by our empirical exercise in Section 1.2, interest rate stickiness can be attributed to various reasons such as switching or menu costs, market structure and regulation. Therefore, we introduce interest rate stickiness in a broader sense by modeling it as in Calvo (1983). This approach has the benefit of reflecting many possible sources of interest rate stickiness in a reduced form. As such, we assume that only a proportion 1-ξ of banks are able to change their lending rates in a given period, whereas the remaining proportion ξ are unable to change their lending rate, which remains fixed at the previous period's value. Accordingly, the composite interest rate in the economy is a weighted average of the current interest rate charged by the banks that can change their interest rate, and the previous period's interest rate used by the banks that cannot change their interest rate.

In order to micro-found the staggered interest rate setting, we assume that there is imperfect competition in the banking sector, where banks offer differentiated loan products as in Gerali et al. (2010) and are able to set their interest rate in the monopolistically competitive loan market. The borrowers then take a composite loan product consisting of these differentiated banking services. The first-order conditions of the bank for interest rates resemble the first-order conditions for prices in a standard New Keynesian setting with price stickiness, and they are given as:

$$R_t^{mi} = \frac{\tau}{\tau - 1} \frac{E_t \sum_{t=0}^{\infty} \xi^t \beta_s^t MC_t}{E_t \sum_{t=0}^{\infty} \xi^t \beta_s^t rm_t}, \tag{2.21}$$

$$R_t^{fi} = \frac{\tau}{\tau - 1} \frac{E_t \sum_{t=0}^{\infty} \xi^t \beta_s^t MC_t}{E_t \sum_{t=0}^{\infty} \xi^t \beta_s^t rf_t}, \tag{2.22}$$

$$MC_t = \lambda_{st+1}[(1 - F_t^B) R_{Dt} + \frac{\nu^b (\phi_t^b / \varphi_t^i)^{(1-\sigma)}}{(B_t^{mi} + B_t^{ei})}](R_t^m)^\tau B_t^m, \tag{2.23}$$

with $\varphi_t^i \in \{\varphi_t^m, \varphi_t^e\}$ for mortgage and corporate lending respectively. The interest rate charged by banks is a function of the present discounted value of present and future "marginal cost" (MC) times the mark-up, where the MC includes the interest rate paid on deposits in a competitive deposit market, and the penalty cost associated with deviating from regulatory capital requirements.

Deposit Insurance Agency insures the deposits, where the assets of the defaulting banks are taken over by the agency and are subject to bankruptcy costs. The difference between the amount of deposits and the value of realised assets is recovered by imposing a lump-sum tax on households.

Final goods producing firms are modeled as a unit mass of perfectly competitive firms, which combine capital and labor to produce the consumption good. The firms rent capital from entrepreneurs, and they are owned by patient households. They produce the final goods using a standard Cobb-Douglas technology:

$$Y_t = E_{A,t} K_{t-1}^{\alpha} L_t^{1-\alpha}, \tag{2.24}$$

where $E_{A,t}$ denotes a standard productivity shock.

Capital goods and housing production comes from competitive firms, owned by patient households, that buy finished goods and produce capital goods and housing subject to quadratic adjustment costs. These firms produce new units of capital and housing using consumption goods, which are then sold to entrepreneurs and households. As such, they represent the supply side of capital goods and housing, and they pin down the equilibrium asset prices.

Macroprudential policy is set by a regulator and includes the LTV limit for borrowers, as well as the sectoral minimum capital requirements and countercyclical capital rules for the banks. For impatient households, the LTV limit follows a static rule:

$$\epsilon_t^m = L\bar{TV}^m. \tag{2.25}$$

Bank capital requirements consist of two components in both sectors. The first part is the minimum sectoral capital requirements $\bar{\varphi^m}$ and $\bar{\varphi^e}$ for mortgage and corporate lending respectively. The second part is the countercyclical capital rules ϕ^m and ϕ^e, which responds to the credit growth in the economy. The associated equations follow as:

$$\begin{cases} \varphi_t^m = \bar{\varphi^m} + \phi^m log(B_t^m/\bar{B^m}), \\ \varphi_t^e = \bar{\varphi^e} + \phi^e log(B_t^e/\bar{B^e}). \end{cases} \tag{2.26}$$

The sectoral capital requirements φ_t^m and φ_t^e implicitly determine the minimum capital requirements in the economy as $\varphi_t = min\{\varphi_t^m, \varphi_t^e\}$, which will be referred to as the Capital Adequecy Ratio throughout the paper.

On top of the aforementioned shocks, we also introduce risk shocks on the corporate and banking sectors $E_{Se,t}$ and $E_{SB,t}$, which affect businesses' and the bank's likelihood of default. We further have an expected capital price shock $E_{EbF,t}$ on the corporate sector, driving the stock market sentiment in the model, and a housing price shock $E_{H,t}$, which is an external shock that directly affects the housing price index. These last two shocks can also be interpreted as measurement errors, i.e. the component of the capital and housing prices that is not explained internally by the model.

Together, we have 12 exogenous shocks across the housing, corporate and banking sectors, all of which follow AR(1) processes.[12]

3 Estimation

3.1 Measurement equations

We use Bayesian likelihood methods to estimate a subset of the model parameters, while the remaining parameters are fixed either at conventional values used in the literature, or at values that

[12]We also experimented with different combinations of shocks across different sectors, e.g. a risk shock on the housing sector, an borrowing constraint shock on the corporate sector, housing and capital depreciation shocks and a net worth shock in the banking sector. The particular set of shocks reported in the paper emerges as the best combination of shocks in terms of model likelihood and providing a reasonable historical variance decomposition for key variables.

generate steady-state values consistent with U.K. data. These values are discussed further in Section 3.2. The fixed parameters mainly correspond to those that affect the steady-state of the model, which is solved numerically since a closed-form solution is not available. We therefore fix this part of the model, and estimate the remaining parameters consisting of shocks, interest rate stickiness and cost adjustment parameters. This procedure allows us to avoid re-evaluating the steady-state for every parameter draw from the posterior distribution (a computationally challenging task), while making business cycle accounting exercises possible in terms of variance decompositions and counterfactual simulations.[13]

In order to estimate the model, we use quarterly data for the U.K. over the period $1998Q1-2016Q2$[14] for ten key macroeconomic and financial variables.[15] For aggregate output Y_t, wages W_t, investment I_t, consumption C_t, as well as house prices $q^{H,t}$, corporate lending $b_{e,t}$ and mortgage lending $b_{m,t}$, we match the data in terms of growth rates with a measurement equation of the form:

$$\Delta X_t^{obs} = \gamma_x + X_t - X_{t-1}, \tag{3.1}$$

with $X \in \{Y, W, I, C, q^H, b_e, b_m\}$ denoting the (log) deviations from the steady-state, X_t^{obs} the observed time series and γ_x the historical average for each variable.[16] For the remaining three variables, namely the official bank rate R_t^D, the effective mortgage lending rate R_t^H, and the effective corporate lending rate R_t^m, we match the data in levels with a measurement equation of the form:

$$Y_t^{obs} = 100(\bar{Y} - 1) + Y_t, \tag{3.2}$$

with $Y \in \{R^D, R^H, R^m\}$ the (log) deviations of interest rates from their steady-state, $\bar{Y}$ the steady-state level of the gross rates and Y_t^{obs} the observed interest rates. Note that we match the official bank rate to the deposit rates in the model.[17]

[13]Alternatively one could use other numerical methods such as a method of simulated moments for a full estimation of the model, which we leave as a potential future extension.

[14]The preceding two years over 1996Q1-1997Q4 are used as a training sample.

[15]Further details on the observable variables can be found in Appendix B.

[16]Since our model does not feature a steady-state growth, these averages are pre-calculated and remain fixed during the estimation.

[17]An alternative approach is to use both the official bank rate and average deposit rates, where the difference between the two is captured with another layer of staggered interest rates. This approach has been adopted in Darracq-Paries et al. (2011), where they find little evidence of staggered rates between these two time series. Therefore in this paper, we directly equate the deposit rates to the official bank rate for simplicity.

3.2 Calibrated Parameters and Prior Distributions

Parameters relating to default costs are based on Mendicino et al. (2018): the depositor cost of bank default γ is fixed at 0.1. The bankruptcy cost of households, businesses and banks μ_m, μ_e and μ_B are set to a common value of 0.3. The discount factor for patient households is 0.995. Several other parameters, for which the data is not informative, also follow from Mendicino et al. (2018). The capital share in production is set to 0.3[18], while the Frisch elasticity of labor η is 1. The labor preference parameters for both types of households φ_s and φ_m are normalised to 1 since they mainly scale the size of the economy. The parameters a_s and a_b are set to 0.5, which determine the share of total default costs paid by saving and borrowing households, respectively.

Some parameters are closely linked with the steady-state of the economy. We use these parameters to generate plausible ratios for some of the key variables. The housing preference parameters for both types of households, v_s and v_m, as well as business and bank dividend payout parameters, χ_e and χ_b, are used to determine the business and mortgage lending to aggregate output ratios. Accordingly, we set $v_s = 0.25$ and $v_m = 0.5$, while the dividend payouts are set to $\chi_e = 0.1$ and $\chi_b = 0.15$. These generate lending ratios of 133% and 86% for corporate and mortgage lending to output, respectively, which are reasonably close to the historical means of the corresponding U.K. ratios over the estimation period with 118% and 81%. At the given values, mortgage lending constitutes 38% of total lending in steady-state. Similarly, we set the housing and capital depreciation rates to $\delta_H = 0.01$ and $\delta_K = 0.04$, which yields an investment to output ratio of 12%, which is close to the historical mean of 17% for the U.K. economy over this period.[19]. The parameters determining market power of the bank, τ_m and τ_F, are both set to 40, whereas the hyperparameters in the cost function are set to $\psi_b = 5$ and $\nu = 0.5$. Finally, we set the household and entrepreneur repayment rates in the household LTV limit and entrepreneur borrowing constraint as 0.01 and 0.05, respectively.[20].

Parameters relating to macroprudential regulation are fixed in our benchmark estimations. Accordingly, for minimum capital requirements, we use a benchmark value of $\bar{\varphi^m} = \bar{\varphi^e} = 0.11$ for both sectors, which is close to the historical minimum capital requirements for the U.K.[21]. We assume

[18] In BoE's COMPASS model (Burgess et al., 2013), this is assigned a similar value of 0.32.

[19] In the model, aggregate investment is calculated as the sum of housing and capital investment. The historical mean ratio for the U.K. is taken from ons.gov.uk for the estimation period.

[20] While we are not aware of any previous studies that calibrate repayment rates, Ingholt (2019) utilises an "amortisation rate" for households, which is calibrated at 0.009.

[21] Available data for capital requirements is taken from Bank of England's website, where we use Basel III common equity Tier I capital ratio after 2014, and Core Tier I capital ratio before 2014. Alternatively, one could use the capital requirements as another observable in the estimation, but we choose to fix these ratios given that the data is only available at an annual frequency before 2014.

that there is no CCyB in place in our benchmark estimations, and the LTV limit for households is fixed at 86%, which corresponds to the historical average over most of this period for the U.K. economy.[22] We fix the borrowing limit on entrepreneurs at the same value as household LTV.

A summary of all fixed parameters is provided in Table 6 in Appendix A. The remaining 33 parameters are estimated using Bayesian likelihood methods to match the data.[23] For the AR(1) coefficients of all exogenous shocks, we use a standard Beta distribution with mean 0.5 and standard deviation 0.2 following Smets & Wouters (2007). The standard deviations of all exogenous shocks are assigned a diffuse uniform prior over the interval $[0, 10]$. The volatility of the default shock parameters σ_e, σ_m and σ_B are assigned inverted Gamma priors with mean 0.1 and standard deviation 2.[24] For the cost adjustment parameters ψ_i and ψ_h, we assume a conventional normal distribution with a mean of 5 and standard deviation 2.[25] For habit formation λ, we use the same Beta prior as in Calvo parameters, and for the impatient household discount factor β_m, we use a tight Beta prior with 0.98 and standard deviation 0.01 to ensure that the prior interval for this parameter remains below the patient household discount factor of 0.995. A summary of all priors can be found in Table 7, Appendix A.

We apply a first-order approximation to solve our model. Since the steady-state of the model is not available in closed-form, the steady-state and first-order approximations are numerically computed for every parameter draw. This increases the computational burden associated with the posterior distributions and complicates the estimation of parameters that affect the steady-state, namely the habit formation, impatient household discount rate, and the i.i.d. shock variances. Therefore, for these five parameters, we only compute the point estimates at the posterior mode. We then leave the parameters fixed at these point estimates before proceeding to the simulation of posterior distributions.[26]

The posterior distributions of the remaining 28 parameters are computed using 8 parallel Monte Carlo Markov Chains (MCMC), each with 250000 draws, where the first 20% of each chain is

[22]Similar to capital ratios, the data to calculate this average is taken from the BoE's website, where we use the residential mortgage LTV ratio, available over the period 2005-2016.

[23]We use the standard Dynare toolkit for our estimations.

[24]These i.i.d. shocks essentially play the same role as the exogenous risk shocks in terms of determining the default rates (with the difference that i.i.d. shocks affect the steady-state levels, while the exogenous shocks do not). Since these two sets of shocks may not be jointly identified, we assign more informative priors for these parameters compared to the standard deviation of exogenous shocks.

[25]See e.g. Smets & Wouters (2007), which uses a normal prior with mean 4 and standard deviation 1.5. Note that our prior is more diffuse compared to BoE's COMPASS model (Burgess et al., 2013), which uses a tight Gamma prior with mean 2 and standard deviation 0.4.

[26]Alternatively, one could fix these parameters similar to the others. But to our knowledge, there are no studies with similar parameters on the U.K. data that could guide the choice of these, and therefore we took this intermediate approach.

discarded as a burn-in sample. The scaling coefficient of the parameter covariance matrix is adjusted to obtain an acceptance ratio of around 35% in each case. Convergence diagnostics for the MCMCs are discussed in Appendix A.1.

3.3 Posterior Distributions for Estimated Parameters

The point estimates, along with the 5 and 95 percentiles of the posterior distributions (referred to as the highest posterior density, or HPD, interval) for the parameters are reported in Appendix A.[27] Of particular interest are Calvo parameters, for which the posterior distributions along with the HPD intervals are shown in Figure 3. We find a Calvo probability of 49.7% for corporate rates, whereas the probability for mortgage rates is 71.8%. This means, on average, banks are able to reset the interest rates on corporate loans once every 1.98 quarters or 5.94 months, while it takes much longer to reset the interest rates on mortgage loans with an average duration of 3.54 quarters or 10.62 months. The HPD intervals are $[5.25, 6.69]$ months for corporate rates and $[8.94, 12.62]$ for mortgage rates.

The shocks are typically estimated with high autocorrelation coefficients, with the exception of bank and entrepreneur risk shocks. In particular, the productivity, housing preference and business net worth shocks have autocorrelation coefficients near unity, implying high persistence. These shocks also emerge as the main drivers of the business cycle for key variables, as will be discussed below. For the capital and housing investment adjustment cost parameters, we find values of 7.92 and 4.85 respectively, implying more sluggishness in housing investment compared with capital investment. For bank capital and bank risk shocks, we obtain relatively wide posterior distributions that remain close to the priors, which suggests that the data is not very informative for these parameters. The remaining 26 parameters are characterised by tighter posterior distributions relative to their priors.

[27] A short discussion on model-generated moments for some of the key variables can also be found in Appendix A.

Parameter	Prior			Posterior			
	Dist	Mean	Variance	Mode	Mean	5% HPD	95% HPD
ζ_m	Beta	0.5	0.2	0.7179	0.7154	0.6645	0.7624
ζ_e	Beta	0.5	0.2	0.4967	0.4922	0.4293	0.5514

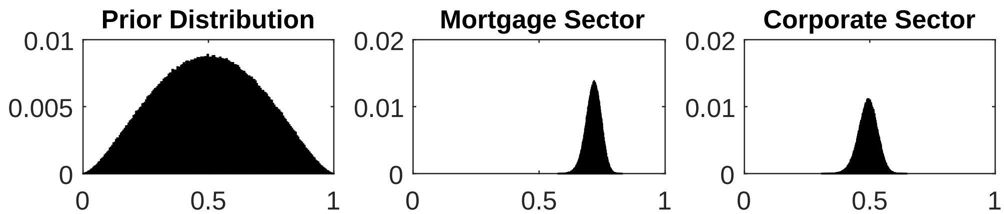


Figure 3. Posterior distributions of estimated Calvo parameters ζ_m (mortgage rate stickiness) and ζ_e (corporate rate stickiness) on interest rate setting.

3.4 Estimated Shocks

In this section we discuss the paths of some of the key estimated shocks over our sample period, which are illustrated in Figure 4 along with their HPD intervals.[28] According to the Figure, it takes the combination of several adverse shocks to generate the crisis of 2007-09 in the model. On the housing side, the main drivers emerge as the housing preference and housing price shocks as both of them fall considerably around the crisis period.[29] The house price shock in our model plays a qualitatively similar role to a measurement error, i.e. it is an external shock that directly hits the house price level. A drop in this shock does not facilitate a negative impact on the economy as will be discussed in the next section, and therefore the adverse effects of the house price drop are picked up by the housing preference shock. Similar to the housing shocks, there is a sizeable drop in the consumption preference shock, which slowly starts to pick up after the crisis but remains persistently low throughout the sample period. Given the similar patterns in housing and consumption preference shocks, these two simultaneous drops can be interpreted as an increased risk aversion to spending by households.[30]

[28]The full set of shocks, along with all of the observable variables are reported in Appendix B.

[29]We tested alternative version of the model with depreciation and expected price shocks on the housing side, in which case the role played by the preference and house price shocks are somewhat reduced but they continue playing a key role.

[30]Note that there is also a substitution effect at play with these two preference shocks: since both preference shocks leave the household wealth unchanged, a negative consumption preference shock increases housing demand whereas a negative housing preference shock increases consumption spending.

On the business side, the entrepreneur net worth shock decreases during the crisis but quickly picks up afterwards, while the expected capital price shock gradually decreases after the crisis. This shock has a redistributional effect from households to the corporate sector, and as such we interpret it as picking up the effects of an external government spending shock in our framework. It is important to note that this shock remains elevated during the post-crisis period compared to its values during the early 2000s.

Finally, the productivity shock decreases during the crisis period. We observe a pattern in the productivity process similar to (but in the inverse direction of) the entrepreneur net worth shock, where the productivity process does not recover after the crisis period and remains lower compared to its pre-crisis level. The post-crisis lower productivity is consistent with the conventional wisdom surrounding a lower productivity in the U.K. (e.g. Bank of England, 2020).

The remaining shocks (not reported in Figure 4) play a smaller role during the crisis period and over the business cycle as a whole. The mortgage and corporate loan mark-up shocks are typically small with the exception of when the Bank Rate falls to near-zero levels. This corresponds to the period where the gap between the Bank Rate and the loan rates (both mortgage and corporate) grows. Accordingly, these two shocks help to generate the interest rate stickiness values reported in Figure 3. The bank net worth and bank capital shocks also play a surprisingly small role, especially surrounding the crisis period. Finally, the housing LTV shock decreases once the adverse shocks hit, which can be interpreted as the borrowing constraint becoming more restrictive during this period. However, this shock does not play a large role in the variance decompositions, as will be discussed below.

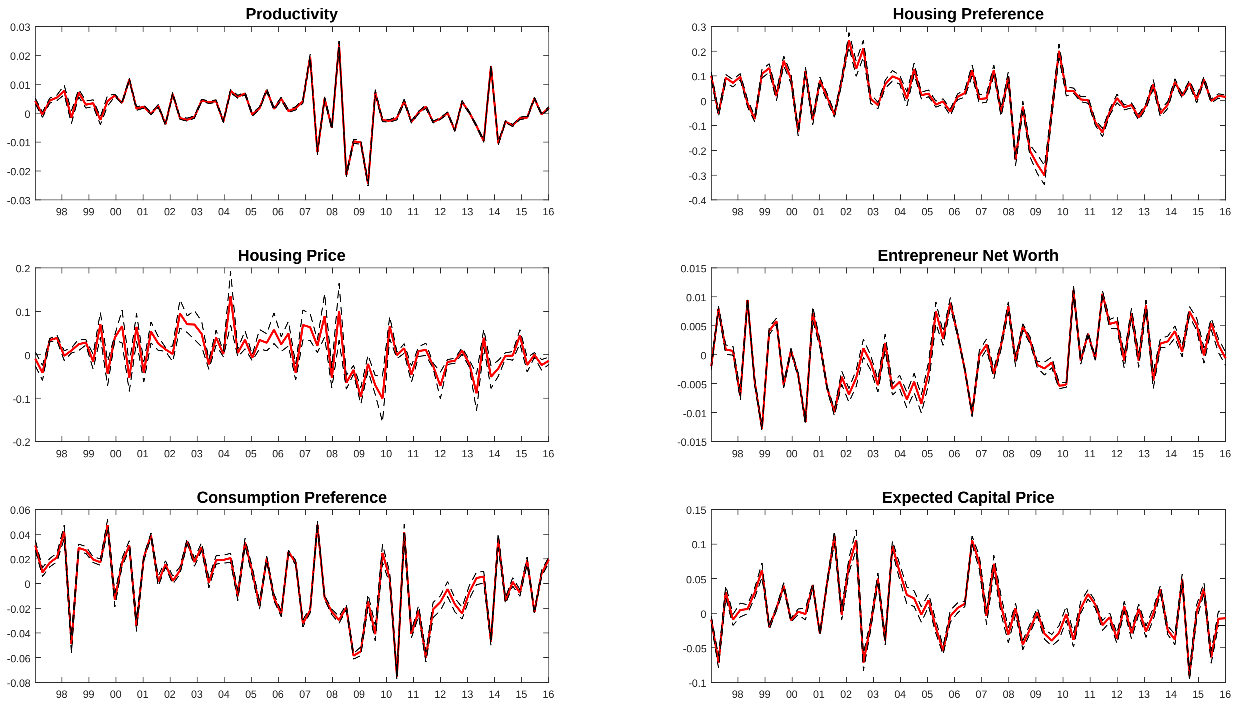


Figure 4. Key estimated shocks driving the financial crisis in the model (dotted lines refer to the HPD interval). The x-axis denotes the dates, and the y-axis denotes the magnitude of shocks.

3.5 Variance Decompositions

We next turn to variance decompositions of some key variables, which brings together the estimated shocks, discussed above, to show how they transmit through the economy. We focus particularly on two variables, namely the mortgage lending and output growth rates, which are shown in Figure 5. The variance decompositions of some other observable variables are also reported in Table 2, which will be discussed further below.

Starting with the mortgage lending growth rate, it is readily seen that the main drivers are housing preference and house price shocks as previously discussed. The external drop in house prices has a ceteris paribus effect of increasing housing demand and, consequently, demand for housing loans. Therefore the house price shocks contribute negatively to the mortgage lending growth during the pre-crisis period when house prices are increasing, and positively during the post-crisis period when the housing price trend reverses. Given the house price shocks, the housing preference shocks are large enough to generate positive lending growth before the crisis, and negative growth after the crisis. Aside from these shocks, bank capital and consumption preference shocks also play a smaller but non-negligible role in terms of driving mortgage lending growth.

Next looking at the output growth rate, we observe that several shocks emerge as important drivers, namely the productivity, entrepreneur net worth and consumption preference shocks.[31] The housing preference shock also plays a role to a smaller extent, and the house price shock becomes particularly important with the onset of the crisis. During the crisis period, all four of these shocks contribute negatively to output growth, whereas bank capital and house price shocks contribute positively. Interestingly, the productivity shock contributes positively throughout the early 2000s until the crisis, while it contributes negatively for a long period after the crisis until mid-2015. The contributions from consumption preference turn positive shortly after the crisis, while the negative ones from housing preference persist. The entrepreneur net worth shock, while playing a relatively large role overall, has periods of both positive and negative contributions both before and after the crisis. Accordingly, the low output growth rate post-crisis is explained by a combination of productivity and housing preference shocks, and to some extent the entrepreneur net worth shocks. The positive contribution from house price shocks during the crisis period works through the channel of boosting housing demand and investment. We interpret this shock on output growth as picking up the effects of loose monetary policy, which would work through the same channel of boosting demand and investment.

Table 2 shows the unconditional decompositions of output and mortgage lending growth rates, along with the other growth rates used as observables in the estimation. It is readily seen that, as discussed above, the output growth rate is mainly dominated by productivity, consumption preference and entrepreneur net worth shocks. The role for both housing shocks are substantially reduced compared to the historical decomposition, which is intuitive since these shocks affect output growth mostly during the period surrounding the crisis. Similarly, the housing preference and housing price shocks are the dominant drivers both for house price and mortgage lending growth rates.

For the corporate lending growth rate, the expected capital price and entrepreneur net worth shocks are dominant as expected, while the wage growth rate is mainly driven by productivity shocks. Finally, the consumption growth rate is mainly dominated by productivity and consumption preference shocks. This is similar to the output growth rate, with the exception that the role of the entrepreneur net worth shock is absorbed by preference shocks.

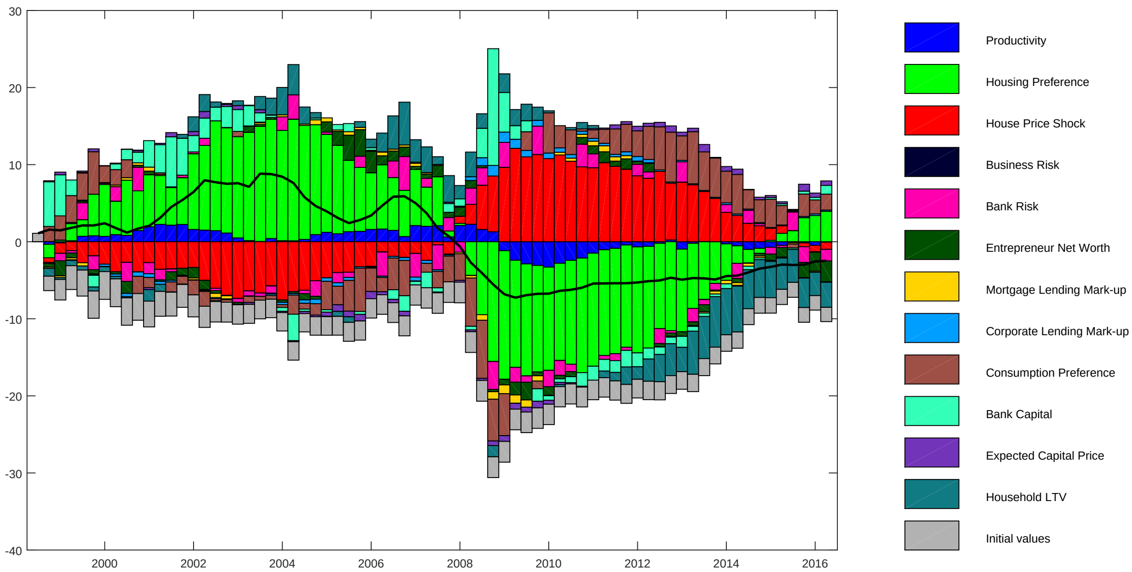
In Table 2, the shocks are grouped into financial and non-financial shocks. We consider the interest

[31] Entrepreneur net worth shocks typically play a large role in other estimated DSGE models with financial frictions, see e.g. Brzoza-Brzezina et al. (2013).

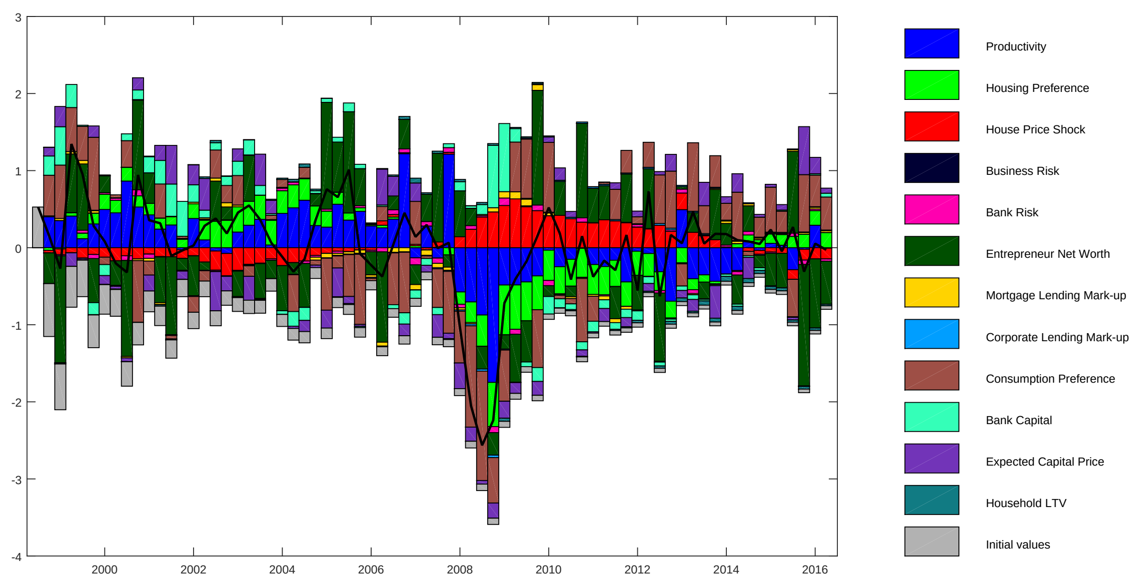
rate mark-ups, bank risk, entrepreneur net worth, housing and expected capital price shocks as financial shocks, whereas the productivity, household LTV, housing and consumption preference shocks are in the non-financial category. Among the real growth rate variables, for output and investment, we observe that financial and non-financial shocks play equally important roles with shares around 50%. For real wage and consumption growth rates, non-financial shocks play a more dominant role, accounting for over 90% of their variance, since the preference shocks are the most important drivers of these variables. Among the financial variables, we observe that non-financial shocks play a more important role in driving housing price and mortgage credit, with shares of 65% and 57.7% respectively. This result is again driven by the fact that the housing preference shock plays an important role for these two variables. Unlike these two variables, corporate credit is driven mainly by financial shocks with a share of 84.6%.

Shocks	Δy_t	Δq_t^H	Δb_t^e	Δb_t^m	Δw_t	Δinv_t	Δc_t
Non-financial	51.32	65.01	15.35	57.73	96.64	50.76	92.09
Productivity	17.58	0.85	12.26	1.78	88.53	2.68	21.07
Housing Pref.	2.01	59.65	2	37.63	0.45	47.33	4.81
Consumption Pref.	31.65	4.49	1.08	11.33	7.58	0.75	66.21
Household LTV	0.08	0.02	0.01	7.19	0.08	0.06	0.12
Financial	48.69	34.99	84.65	42.08	3.36	49.25	7.91
Mortgage Rate Mark-up	0.06	0	0.18	0.08	0.01	0.02	0.01
Corporate Rate Mark-up	0.01	0.01	0.06	0.15	0	0.01	0
Bank Risk	0.18	0.12	0.03	5.62	0.48	0.01	0.44
Entr. Net Worth	33.45	0.18	16.57	1.66	0.62	1.72	0.55
Housing Price	1.66	33.35	1.9	10.81	0.73	39.78	4.1
Bank Capital	9.7	1.26	26.11	23.48	1.24	7.12	2.5
Exp. Capital Price	3.63	0.07	39.8	0.28	0.28	0.53	0.19

Table 2. Unconditional variance decompositions of key variables. The variables we consider are output growth Δy_t , house price growth Δq_t^H, corporate lending growth Δb_t^e, mortgage lending growth Δb_t^m, wage growth Δw_t, investment growth Δinv_t and consumption growth Δc_t . The shocks are grouped into financial (mark-ups, bank risk, entrepreneur net worth, housing and expected capital price) vs. non-financial (productivity, preference and household LTV) shocks.



(a) Mortgage lending growth rate.



(b) Output growth rate.

Figure 5. Historical variance decompositions of mortgage lending and output growth rates over period 1998Q1-2016Q2.

4 Macroprudential Policy & Welfare Analysis

In this section we analyse the effects of macroprudential policy tools on aggregate household welfare, output and credit. We discuss the effects of macroprudential tools in two steps. First we discuss optimal policy using a welfare-based objective function and find the objective-maximising macroprudential policies individually and jointly. This allows us to discuss whether the appropriate combination of macroprudential tools can be welfare improving. Second, using the optimal policies from this analysis, we run a number of counterfactual simulations to analyse what effect the macroprudential policies would have had on the economy if they had been in place before the crisis.

4.1 Optimal Policy

To assess the effects of macroprudential policies, we start by defining household welfare as follows:

$$W_t = \frac{W_t^s C_t^s + W_t^m C_t^m}{C_t^s + C_t^m},$$

where W_t^i and C_t^i with $i \in \{s, m\}$ refer to the welfare and consumption of patient and impatient households respectively. Accordingly, our welfare measure is a weighted average of patient and impatient households, where the weights are determined by the consumption shares of households.[32] Given this definition of aggregate welfare W_t, we use a standard linear-quadratic function as our objective:

$$E[W_t] - \omega\sqrt{Var[W_t]}.$$

The first term corresponds to the expected value of welfare (with a first order approximation, this is equal to its steady state value), and the second term is its volatility.[33] While the variation in the steady state captures the static effects of macroprudential policies, welfare volatility allows us to also account for their potential dynamic effects. We consider two cases for the weight on volatility: (i) $\omega = 0$, which focuses on the steady-state level of welfare, and (ii) $\omega = 0.1$, which shows the effects of including welfare volatility on the resulting optimal policies.

We first compute the optimal values of macroprudential tools when they are used individually.[34] The results are reported in Table 3. When $\omega = 0$ (no weight on welfare volatility), we find that the optimal household LTV ratio is looser at 89.4% compared to its baseline level of 86%, and

[32] This definition of welfare follows from Mendicino et al. (2018). Our main results are robust to how the households are weighted in calculating the aggregate welfare. See Appendix E for further discussion.

[33] The expectation and variance terms are the moments around the ergodic distribution of the model.

[34] Details on optimal policy and steady-state calculations can be found in Appendix E.

it comes with only a marginal improvement on welfare with 0.014%.[35] For the sectoral capital requirements (SCRs), we find relatively large optimal values (compared to the baseline of 11%) of 20.7% and 15.5% for mortgage and corporate lending, respectively, while the optimal CAR turns out to be 15.5%. The welfare improvement among the three policies is largest when maximising over mortgage SCR with 7.47%, and smallest when maximising over corporate SCR with 3.33%. As such, our results suggest that sectoral SCRs on mortgage lending are more important than those of corporate lending from a household welfare perspective.

When we also place some weight on welfare volatility with $\omega = 0.1$, we observe that the optimal LTV ratio becomes tighter compared to $\omega = 0$, and it remains very close to its benchmark value of 86%. Further, for both SCRs and CAR, we find smaller optimal values compared to the $\omega = 0$ case, suggesting a trade-off between welfare level and welfare volatility. Nevertheless, these results indicate that there is a well-defined optimal policy in terms of LTVs, SCRs and the CAR. As an illustration, Figure 6 shows this result with respect to housing SCR and CAR. It is readily seen that the expected aggregate welfare attains a maximum at the optimal values specified in Table 3.[36,37]

	ω	0	0.1
Parameter			
LTV		89.4 % (0.014 %)	86.6 % (0.001 %)
SCR-Mortgage		20.7 % (7.47 %)	17.6 % (4.26 %)
SCR-Corporate		15.5 % (3.33 %)	16.7 % (3.22 %)
CAR		15.5 % (5.11 %)	14.5 % (3.82 %)

Table 3. Maximising over prudential policy parameters, one at a time. LTV refers only to housing loan-to-value limit in this case, and we leave the corporate LTV at its baseline level of 86% throughout. The baseline policies are LTV= 86%, and CAR= 11% (i.e. both SCRs are set to 11%). The numbers in parentheses indicate the improvement in aggregate welfare relative to the baseline.

Given the individual optimal policies, we next investigate whether coordinating these policies (i.e. optimising them jointly) may lead to further welfare improvements. Table 4 reports the joint optimal combination of LTV, CAR and SCRs for the same cases with $\omega = 0$ and $\omega = 0.1$. With no weight

[35] Recall that the LTV limit in our model is assumed to be an always binding constraint. Our results on LTV here may be sensitive to the formulation of this, but we leave an occasionally binding LTV ratio to future research.

[36] The figures for welfare volatility, as well as for the LTV limit and corporate SCR are omitted here for brevity, but similar results follow.

[37] Note that no results for the CCyB are included in Table 3. Since the CCyB is a dynamic policy, it does not affect the steady-state levels of lending rates or welfare. Therefore, there is no optimal CCyB without a weight on volatility. When there is some weight on volatility with $\omega > 0$, the optimal CCyB is to react as strongly as possible to changes in mortgage and corporate lending rates, since a stronger CCyB always reduces the volatility of lending rates and welfare.

on volatility, we find that the optimal LTV ratio is looser compared to the previous case, with 91.25% (compared to 89.4%), the mortgage SCR is higher with 21.25% (compared to 20.7%), and the corporate SCR reduces to its lower boundary of 5% (which also implies a CAR of 5%). This scenario puts an excessive weight on the mortgage lending requirements and, as seen from Table 4, it leads to a larger welfare improvement of 8.01%, compared with improvements ranging from 0.014% to 7.47% for individual optimal policies.

With a positive weight on welfare volatility, i.e. $\omega = 0.1$, we find that the optimal LTV ratio is even looser with 94%, while the sectoral SCRs are now closer to each other with 15.88% and 12.5% on mortgage and corporate lending, respectively (and the implied CAR is 12.5%). This suggests that the excessively loose SCR on corporate lending in the previous case comes at a cost of higher volatility, and therefore introducing some weight on volatility increases the optimal corporate SCR to a more reasonable level. The welfare improvement in this case turns out to be 4.8%, which is again larger than the improvements obtained by individual optimal policies ranging from 0.001% to 4.26%. This establishes our key result for this section: the appropriate combination of macroprudential tools achieves a higher welfare improvement compared to a situation when the tools are used individually.

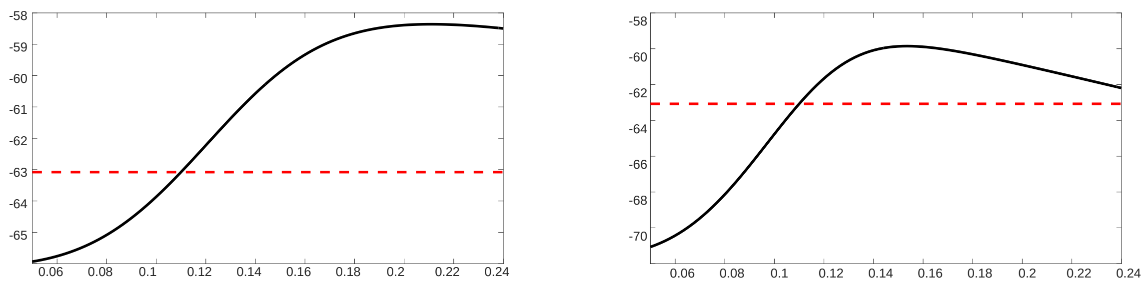
The results in this section also point towards a trade-off between achieving a higher level of welfare and minimising welfare volatility. In most studies, the focus is generally on how policies can stabilise volatility, taking as given the steady-state levels.[38] Our results using the ad hoc objective function instead suggest that reducing volatility may come at a cost in terms of the steady-state welfare level. However, it is important to recall that we use a first-order approximation of the model, therefore any changes in volatility have no effect on the level of welfare in the model. With higher-order approximations, reductions in volatility may be associated with higher levels of welfare, which may reduce the trade-off between the welfare level and volatility that we find for our ad hoc objective function. We leave a further exploration of this trade-off to future research.

Using the optimal policies from this section, we next run a set of counterfactual simulations to analyse whether the macroprudential tools also achieve a better outcome over the business cycle.

[38] This is typically accompanied with an implicit assumption that the economy's steady-state is already optimal, i.e. it is the first-best outcome, which can be achieved through appropriate tax and subsidy schemes. In our case, we find that reducing volatility may push the economy further away from the first-best outcome.

Weight on volatility ω	0	0.1
Parameter		
LTV	91.25 %	94.06 %
SCR-Mortgage	21.25 %	15.88 %
SCR-Corporate	5 (Min. allowed) %	12.50 %
Welfare Improvement	8.01 %	4.8 %

Table 4. Maximisation over SCRs and LTV at the same time.



(a) Welfare level (y-axis) as a function of the housing SCR (x-axis).

(b) Welfare level (y-axis) as a function of CAR (x-axis).

Figure 6. Sectoral capital requirements on mortgage lending with a baseline of 11%. Welfare maximising value is 20.7% with a weight of 0 on volatility. It decreases to 17.6% with a weight of 0.1 on the volatility. **Welfare improvement: 7.47% and 5.11% respectively.** The red lines correspond to the welfare level at the benchmark policies.

4.2 Counterfactual Simulations

In this section we analyse, through the lens of our model, what would have happened if the macroprudential tools, set at their welfare-maximising levels as found in the previous section, were in place before the financial crisis. To this end, we use the joint optimal policies with $\omega = 0.1$, hence we set the LTV limit to 94%, housing SCR to 15.8% and corporate SCR to 12.5%. We use the parameters at the estimated posterior mode as reported in Table 7 and consider several counterfactual simulations as follows: we use the smoothed shocks implied by the estimated parameter values, and the shocks remain fixed at these values as our benchmark case. We then re-simulate the economy, where the system is subject to the same set of shocks, but prior to the crisis, the optimal macroprudential policies are in place instead of the benchmark policies.

We assume that the optimal policies are always in place from the beginning of the sample. The patterns of some key variables under the baseline and counterfactual scenarios are reported in Figure 7. Our results in Section 4.1 suggest that the optimal macroprudential mix we found prescribes a looser borrowing constraint relative to the benchmark, through a higher LTV limit coupled with a more resilient banking system through higher SCRs (and therefore CAR). This is exactly the result that comes out of our counterfactual simulation: due to higher capital requirements, the bank default rate decreases compared to the benchmark scenario. The higher housing SCR and looser LTV limit have opposing effects on household borrowing, and looking at Figure 7 we observe that the looser LTV limit dominates, resulting in a higher level of household borrowing.

While the corporate SCR is higher compared to the benchmark scenario, the relative increase is smaller compared to the housing SCR. This leads to a substitution effect on the banking side, where the bank prefers to shift its portfolio from mortgage lending to corporate lending. It is readily seen that this substitution effect dominates the increase in the absolute level of corporate SCR (from 11% to 12.5%), and business borrowing ends up higher under the counterfactual scenario compared to the baseline.

The increased borrowing also boosts housing and capital investment, which feeds back into the consumption of both impatient (borrower) and patient (lender) households, as well as aggregate output. The default rate of households increases under the counterfactual since the amount of borrowing is higher, but the increased default rate is mostly offset by the increased consumption and a lower bank default rate (which has a cost on the households). Therefore, borrowers are almost equally well-off under the counterfactual, while lenders are better off due to increased consumption and investment. This results in a higher output and total welfare under the counterfactual scenario, even though the drops associated with the crisis are at similar levels compared to the baseline scenario. Accordingly, a looser borrowing limit combined with a more resilient bank results in an overall beneficial outcome.

Looking at the percentage changes for our target variables listed in Figure 7, it is readily seen that the average volumes of lending as well as aggregate output and welfare are all higher under the counterfactual scenario. However, a similar fall of these variables after the financial crisis is still present. These results suggest that, if different counterfactual policies were in place before the crisis, some aggregate indicators would have been improved but, within our model, the crisis would not have been prevented.[39,40] There are some previous studies in the literature that find a more

[39]An alternative optimal policy analysis would involve finding a scenario under a counterfactual simulation that balances the level and volatility of welfare. This is omitted in our paper for brevity.

[40]We also experimented with an alternative simulation exercise, where the optimal policies are introduced over a 5-year period between 2001 and 2006. As might be expected, we obtain the same (positive) direction in all target variables both in terms of level and volatility when the policies are phased in this way, but the resulting magnitudes

significant role for macroprudential policy in preventing the house price boom and the subsequent crisis by considering a wider range of policy tools. For example Aikman et al. (2019a) note that, while tighter LTV limits and capital requirements may have a small impact during a boom period due to the twin nature of the household debt and house price booms, other tools such LTI limits and housing affordability criteria may have been more efficient in preventing the crisis.

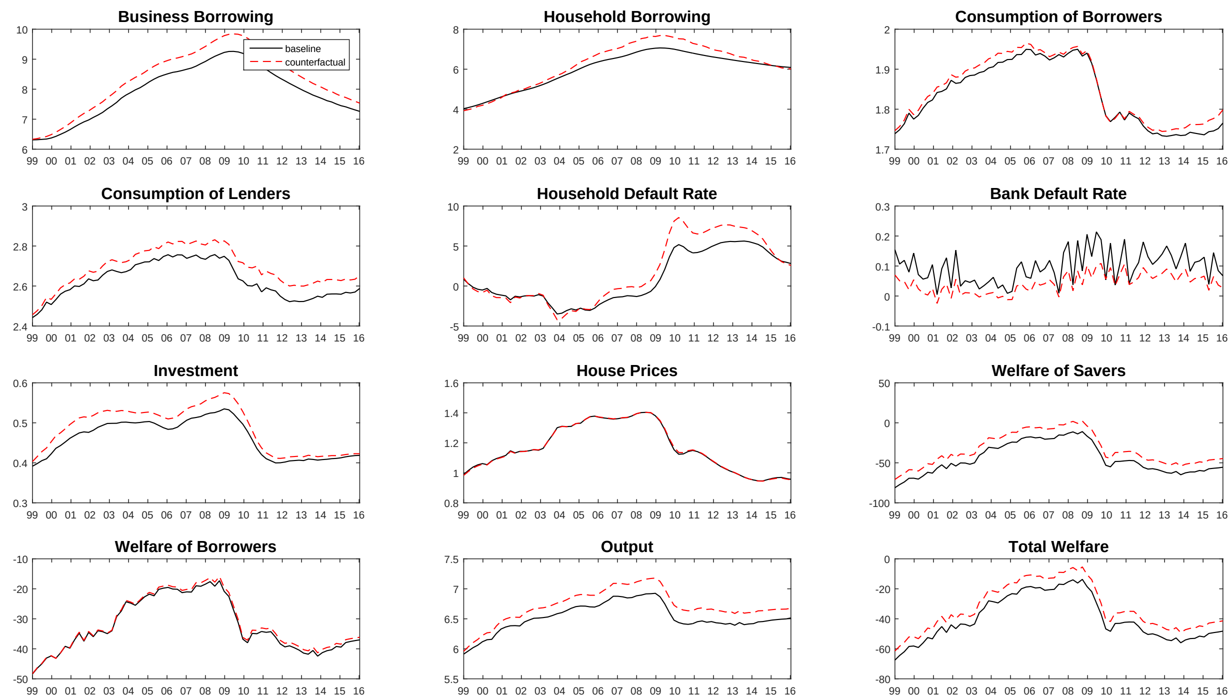


Figure 7. Counterfactual: using optimised values with 0.1 weight on volatility. $\phi^m = 15.8\%$ (mortgage SCR), $\phi^e = 12.5\%$ (corporate SCR), $\bar{LTV}^m = 94\%$ (household LTV). For target variables, the average increases over the sample period are 4.9% for corporate credit, 4.2% for mortgage credit, 2.8% for output and 17.6% for household welfare.

Next, in order to investigate the effects of the CCyB at the business cycle frequency, we analyse what happens with the introduction of the CCyB when the optimal LTV and SCRs are already in place. To this end, we consider three scenarios with (i) a sectoral CCyB on corporate lending, (ii) a sectoral CCyB on mortgage lending, (iii) a CCyB in both sectors, set at the same level. Given our policy function, the CCyB reacts to deviations of corporate and mortgage lending from its steady state level. We set the CCyB level to generate a standard deviation of approximately 2.5% in minimum requirements, which is obtained by tuning the reaction parameters in the policy

are smaller since the policies are in place for a shorter duration. In both cases with and without phasing-in, we obtain a welfare improving outcome under the optimal policy scenarios.

function.[41] The results are reported in Table 5: we observe that introducing a CCyB when the other optimal policies are already in place improves the outcomes further in terms of levels. In particular, aggregate output and welfare levels are improved when the CCyB is active in both sectors, as well as when it is active in each sector individually. However, it is worth noting a downside with using the CCyB in this form: during the sample period, the mortgage and corporate borrowing volumes continue increasing above their steady-state levels during the pre-crisis period. While they start declining with the onset of the crisis, they are still well above their steady-state values once the crisis hits, and they remain above that level throughout the whole sample. As such, a CCyB that reacts to deviations of borrowing volumes from their steady-state level leads to capital requirements that increase even during and after the crisis. In other words, the CCyB rate is never fully released to zero, even in the crisis. This issue may downplay the impact of a CCyB.[42]

Variable	% Change in Level	Variable	% Change in Level
Baseline optimal minimum SCRs+LTV		CCyB 2.5%, mortgages	
Corporate Credit	4.9	Corporate Credit	7.3
Mortgage Credit	4.2	Mortgage Credit	0.05
Output	2.8	Output	3.9
Household Welfare	17.6	Household Welfare	19.4
CCyB 2.5%, both sectors		CCyB 2.5%, corporate	
Corporate Credit	5.8	Corporate Credit	3.2
Mortgage Credit	4.5	Mortgage Credit	8.1
Output	4.1	Output	2.7
Household Welfare	21.2	Household Welfare	19.1

Table 5. Does a CCyB improve outcomes when other optimal requirements are in place?

[41] This results in a parameter value of 0.051 that reacts to deviations of mortgage lending from its steady state, and a parameter value of 0.128 for corporate lending.

[42] Alternative reaction functions such as a CCyB on the growth rate of lending rates could resolve the issue. For example, Ferreira & Nakane (2018) experiment with different anchors for the CCyB, such as growth rates and deviations from the steady-state. They find that lending growth acts as the most robust anchor for the CCyB. In this paper, we abstract away from such alternative formulations of the CCyB.

5 Impulse Response Analysis

5.1 Interest Rate Stickiness and Shock Propagation

In this section we discuss the effects of individual shocks on key variables through impulse response functions to get a better understanding of the channels through which shocks propagate and how macroprudential tools work to offset the impact. We first start with the effects of interest rate stickiness on shock propagation. Given the significant rate of stickiness in U.K. data, as shown by our results in Sections 1.2 and 3.3, this can be an important channel that affects the transmission of shocks throughout the economy. We focus on three shocks across different sectors of the economy: a housing preference shock on the housing side, an expected capital price shock on the corporate side, and a bank capital shock on the banking side. We report the effects on several key variables with and without interest rate stickiness in each sector. In particular, we focus on four scenarios in terms of interest rate stickiness: (i) the estimated degrees of stickiness, (ii) a low degree of stickiness in the housing sector, (iii) a low degree of stickiness in the corporate sector and (iv) a low degree of stickiness in both sectors.[43]

Figure 8 reports the effects of a negative housing preference shock. The shock directly lowers the demand for borrowing by households, which translates into a drop in house prices. Since the shock leaves the overall level of household wealth unchanged, households increase their consumption spending. The effects on these three variables are similar with different degrees of stickiness, since the shock originates in the household sector and does not transmit through interest rates. In response to the drop in housing demand, the bank lowers the household interest rate and this is where we start to see the effects of interest rate stickiness: the bank is able to cut interest rates the most when interest rate stickiness is low in both sectors, while the drop in interest rates is smallest when the stickiness is at the estimated level in both sectors. In response to the drop in house prices, housing investment also decreases. Since aggregate investment consists of housing and capital investment, the drop in housing investment translates into a drop in aggregate investment, the magnitude of which depends on the degree of stickiness.

Similar to the household interest rates, the bank also ends up lowering corporate rates for two reasons: first, keeping the corporate rates constant while lowering mortgage rates would result in a substitution effect towards the housing sector in terms of credit demand, and therefore the bank has an incentive to cut corporate rates in response to a decline of mortgage rates. Second, the volume of business borrowing decreases given the lower aggregate investment, and therefore the bank prefers

[43] We use a stickiness rate of 15% in the low stickiness scenarios. Lower values lead to indeterminacy.

lower business lending rates to make up for the loss in demand. The net effect on aggregate output in general depends on the positive effects on aggregate consumption and the negative effects on aggregate investment. Under our parameterisation, the negative effects dominate and we see a reduction in aggregate output following the housing preference shock. The effect is smallest when the degree of stickiness is small in both sectors, and the stickiness in mortgage rates has the highest impact on aggregate output. This is intuitive since the shock starts from the housing sector, and hence the largest spillover effect takes place when the bank is unable to cushion the shock through mortgage rates.

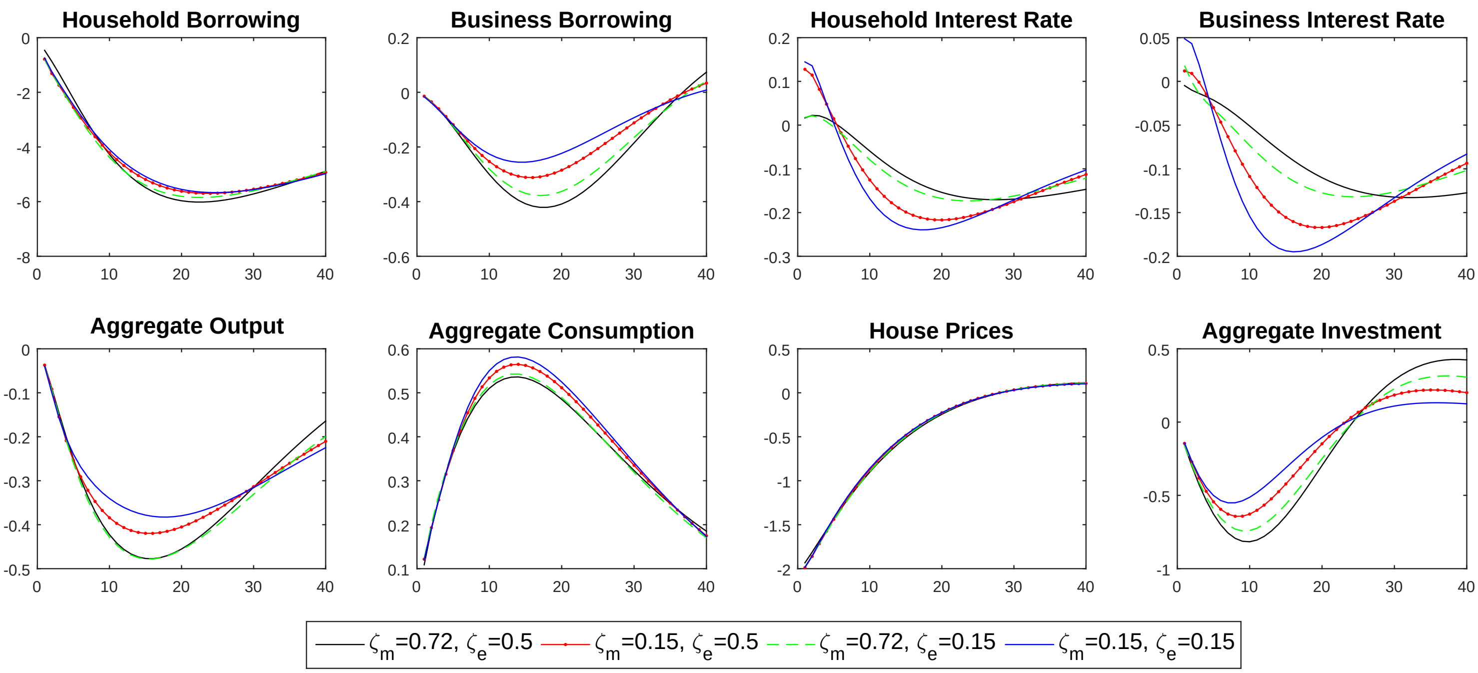


Figure 8. Impulse responses to a negative housing preference shock.

Next we turn to Figure 9, which reports the effects of a negative capital price shock. Since the shock originates in the corporate sector, the immediate effects take place on the borrowing volume of businesses and aggregate investment: these variables decrease in all cases independent of the degree of stickiness. This effect spreads through two channels: first, the lower capital investment results in a substitution effect towards housing investment, which pushes up house prices. As a result, households shift some of their spending from housing to consumption in the short run, which results in a higher consumption and lower household borrowing. In response to the lower volume of household borrowing, and to prevent the substitution effect from lower corporate rates, the bank cuts the housing lending rates. In the medium run after around 10 quarters, the effects of lower household lending rates start to kick in and the households start shifting away from consumption back into housing. The largest fluctuations in household borrowing takes place when both interest rates are at their estimated value (i.e. when they are stickiest). Interestingly, the stickiness rate in mortgage lending again plays a more important role than corporate lending, even though the shock originates in the corporate sector. The overall effects on output are only marginally affected by interest rate stickiness in this case, since the drop in investment is substantially larger than the short-term increases in consumption, which means the largest effect (through investment) does not transmit through interest rates.

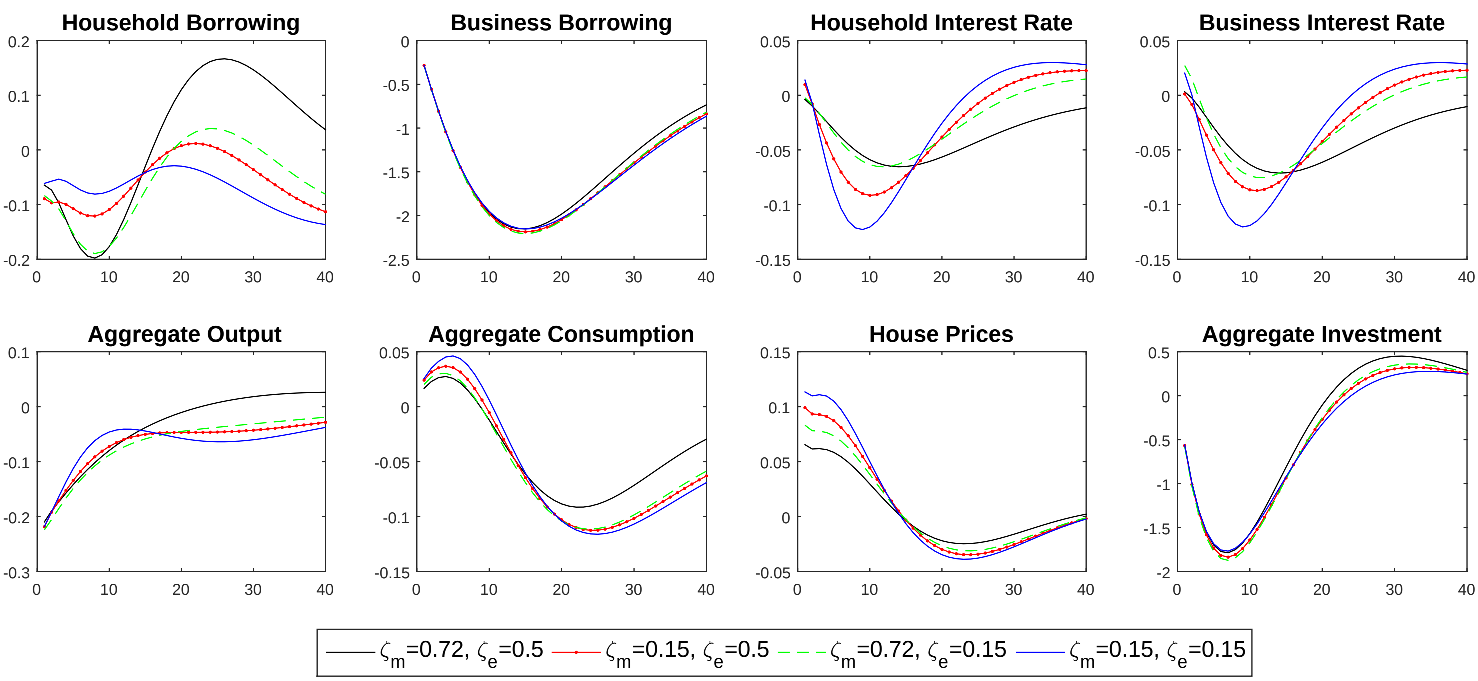


Figure 9. Impulse responses to a negative expected capital price shock.

Finally, we discuss the effects of a negative bank capital shock, reported in Figure 10. In this case, the shock stems from a decrease of bank capital, to which the bank responds by increasing the lending rates in both sectors since it is not able to lend out as much. This unambiguously transmits through the rest of the economy in a negative manner, where the interest rates increase depending on the degree of stickiness (largest increase when stickiness is lowest). The immediate result is a lower borrowing volume in both sectors. Investment and house prices both go down in response to the higher borrowing rates. In terms of consumption, there are again two effects: the lower household borrowing results in a substitution effect in the households' spending bundle, but at the same time the lower aggregate investment results in lower household wealth. It is clear from the figure that the latter effect dominates and household consumption goes down, which also results in a lower aggregate output. Unlike the previous two cases, we see the largest effects on output when interest rate stickiness is lowest. In the previous cases, the bank reacts through interest rates by trying to mitigate the adverse effects of shocks in other sectors, hence the effects are strongest when interest rates are stickiest. In this case, the bank reacts by trying to shift the adverse effects from itself onto households and businesses, and therefore the effect turns out strongest when interest rates are the least sticky.

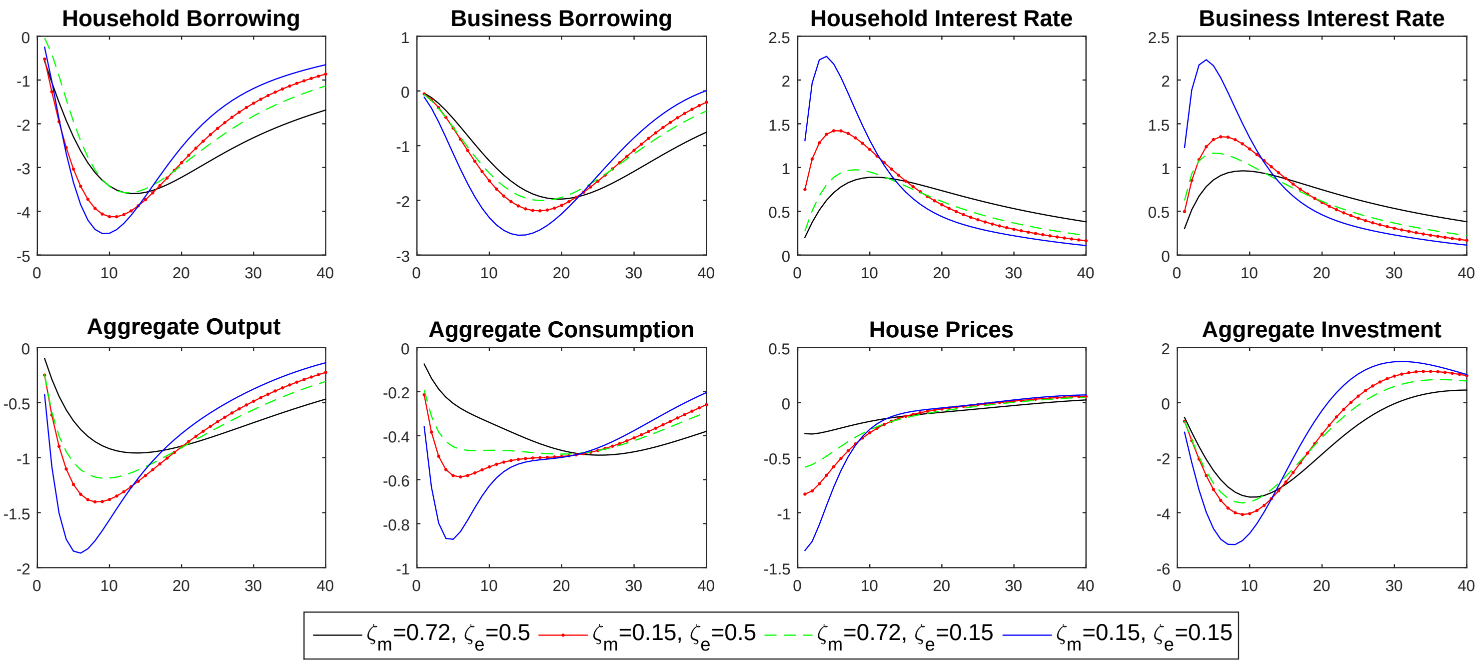


Figure 10. Impulse responses to a negative bank capital shock.

5.2 Interest Rate Stickiness and Sectoral Capital Requirements

Given the importance of interest rate stickiness for the transmission of shocks, in this section we analyse how interest rate stickiness affects the impact of macroprudential policies. We focus on the policies that transmit through interest rates in our model, namely (static) sectoral capital requirements and sectoral countercyclical capital buffers. In this case, we focus on the response of lending volumes to a (positive) bank capital shock only, although the analysis can be extended to other shocks as well.

Figures 11 and 12 report the effects of low (11%) and high (15%) SCRs on corporate and mortgage lending, respectively. Two important observations stand out from the figures: first, higher SCRs in either sector generally lower the effect of a (positive) bank capital shock on lending volumes in both sectors. Second, the difference between impulse responses under high and low SCRs is generally larger when interest rate stickiness is lower (i.e. the difference between the green and blue curves tends to be larger than the difference between the red and black curves). This suggests that stickier interest rates dampen shocks emanating in the banking sector to the real economy, but the effect decreases with higher minimum requirements since the marginal change in rates in response to a shock becomes smaller.

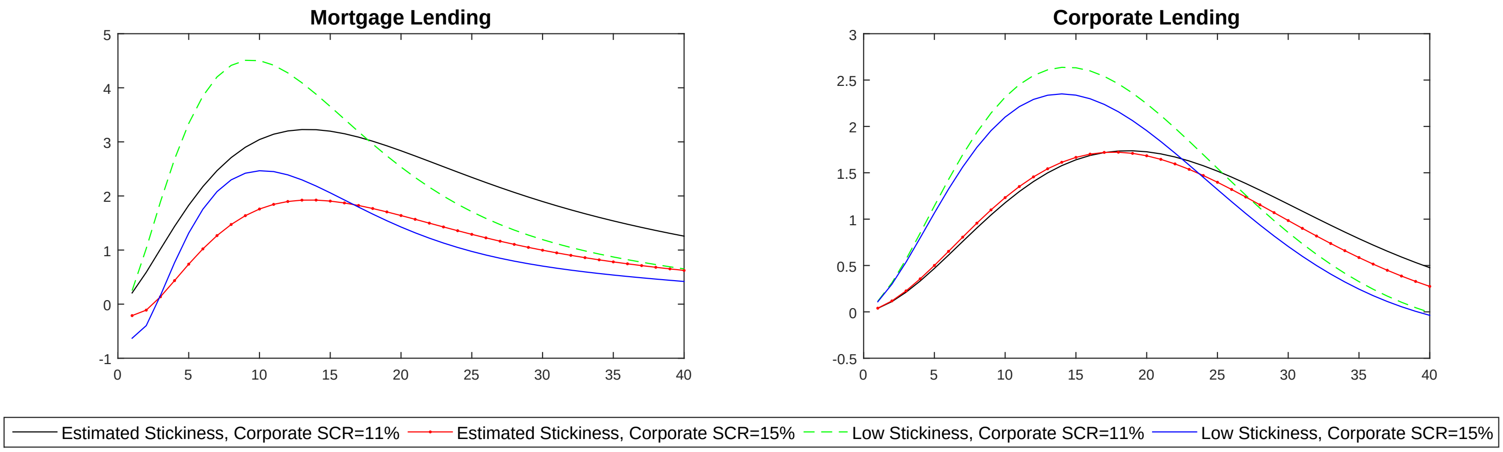


Figure 11. The impact of a corporate SCR on lending volumes with high and low levels of interest rate stickiness in response to a positive bank capital shock.

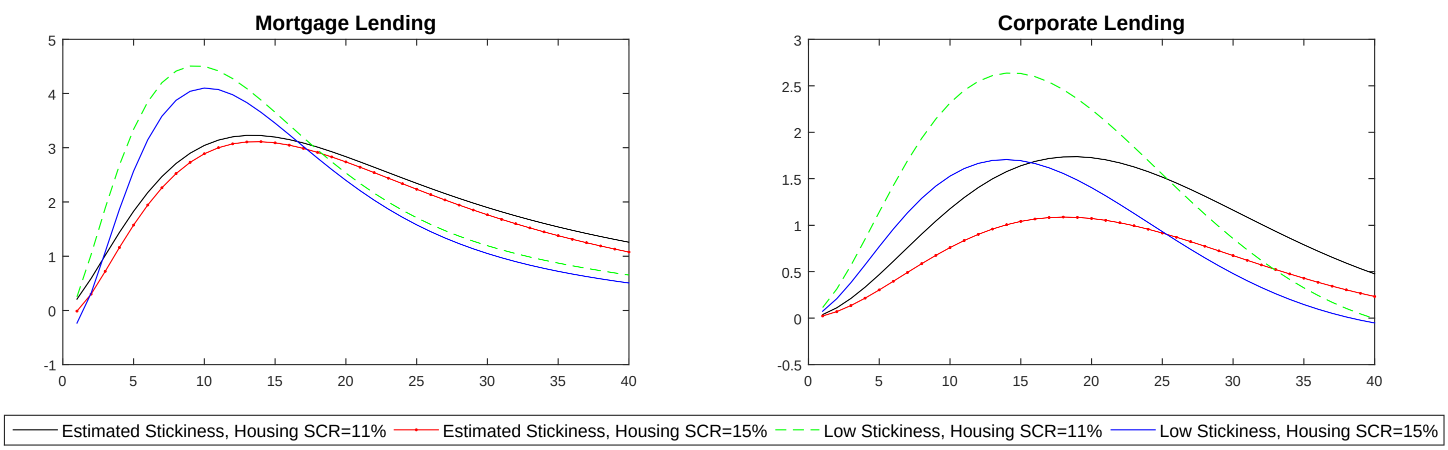


Figure 12. The impact of a housing SCR on lending volumes with high and low levels of interest rate stickiness in response to a positive bank capital shock.

Similarly, Figures 13 and 14 report the effects of no sectoral CCyB and a 2.5% sectoral CCyB on housing and corporate lending, respectively.[44] We observe in this case that, for both sectors, introducing a sectoral CCyB lowers the response of lending in that sector in light of a bank capital shock. However, there are two important differences compared to the static SCRs: first, the

[44]Similar to the previous section, the 2.5% CCyB is obtained by tuning the parameter in the reaction functions to generate a standard deviation of 2.5% in the capital requirement rates.

differences with and without interest rate stickiness are smaller compared to the SCRs. Second, unlike the SCRs, we observe a substitution effect towards the other sector in this case. An increase in the corporate lending CCyB leads to a lower volume of corporate lending (in both cases with and without stickiness). In response, the bank makes up for the reduction in corporate lending by increasing its mortgage lending volume. Similarly, a higher mortgage CCyB reduces the volume in mortgage lending (again in both cases with and without stickiness), while the corporate lending volume increases. Hence in both cases, the bank responds to an increased sectoral CCyB by shifting its lending portfolio towards the other sector. This result emerges due to the gradual nature of CCyBs: since the tool builds up slowly over time, interest rate stickiness has a much smaller impact and the graduality allows the bank some time to substitute its lending volume towards the other sector.

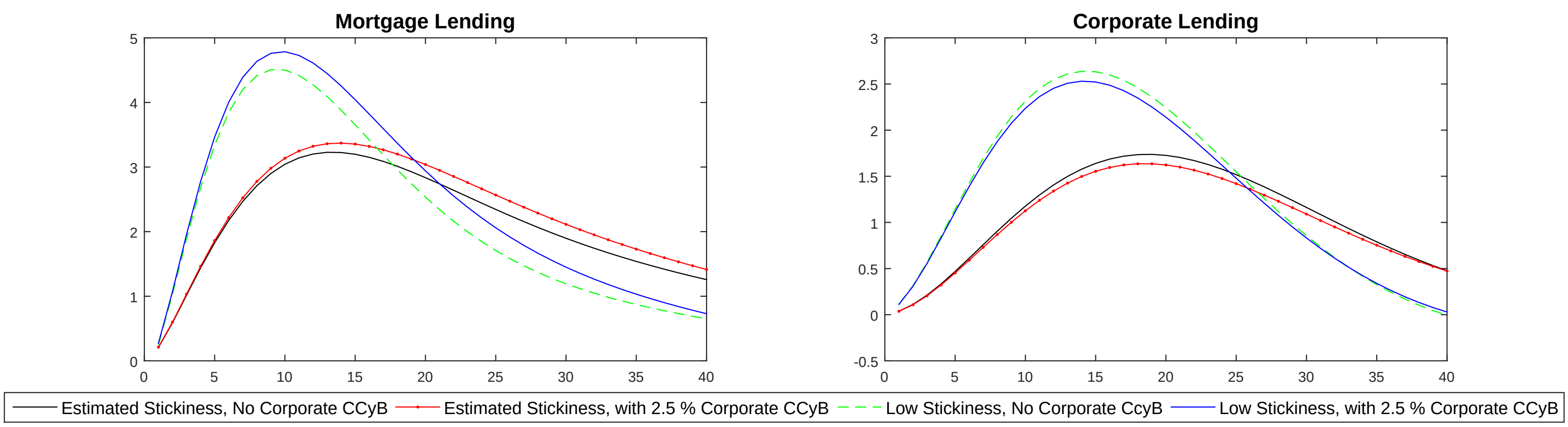


Figure 13. The impact of a 2.5% corporate CCyB on lending volumes with high and low levels of interest rate stickiness in response to a positive bank capital shock.

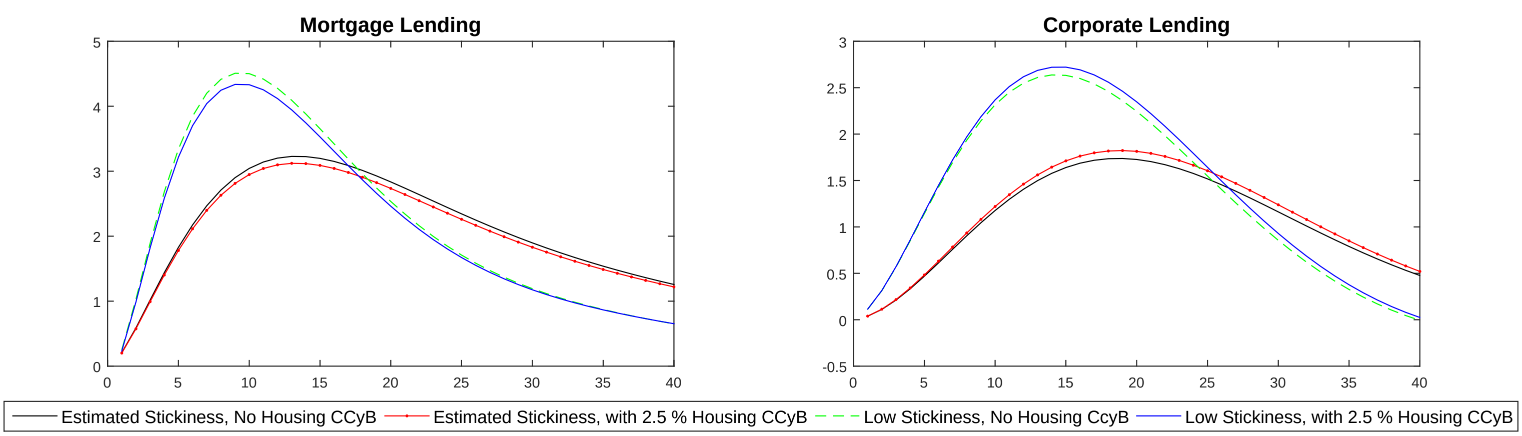


Figure 14. The impact of a 2.5% housing CCyB on lending volumes with high and low levels of interest rate stickiness in response to a positive bank capital shock.

These results suggest that interest rate stickiness plays an important role both in terms of the transmission of shocks through the economy, and also in terms of the effectiveness of macroprudential tools that work through interest rates, which are SCRs and CCyBs in our model. In particular, interest rate stickiness reduces the peak impact of a change in macroprudential policy that relies on interest rates for transmission (such as the bank capital shock), but also prolongs the adjustment period. The impact of interest rate stickiness appears to weaken the higher the starting level of capital requirements. Overall, this presents an important channel for the design of macroprudential policies and particularly for tools that are affected by the degree of interest rate stickiness through long-term contracts.

6 Conclusion

Assessing the effectiveness of the macroprudential toolkit is essential for ensuring that the risk of future financial crises is reduced to the largest degree possible. The regulatory reforms since the Global Financial Crisis, both at the international and domestic level, have substantially increased the instruments available to policymakers. Consequently, the extent of potential interactions if tools are in effect at the same time has also gone up significantly. Policymakers need to take such interactions into account when setting the optimal levels of their respective policies.

In this paper, we have assessed some of the interactions of macroprudential tools, including sectoral capital requirements, the countercyclical capital buffer, as well as loan-to-value limits, in a sectoral DSGE model with interest rate stickiness. Staggered interest rates are an important friction that influence the transmission of capital instruments that primarily work through interest rates. The model allows us to calculate the optimal (welfare maximising) calibration of these policies, and perform counterfactual exercises to assess their effects on the economy. While these instruments lead to the expected improvement in economic indicators, they would not have been able to completely prevent the Great Recession within our model.

We have left a number of possible extensions to future research. First, additional instruments, such as loan-to-income limits, could be introduced. Second, some of the policies in our model could be implemented in different ways. For example, the LTV limit could be designed as an occasionally binding constraint, and the setting of the CCyB could be modelled in a more asymmetric way, i.e. a slow build-up phase followed by a sudden release once a downturn occurs. Third, different objective functions could be tried to determine the optimal setting of different policies. In particular, our optimal policy analysis suggests that there may well be a trade-off between improving welfare and reducing welfare volatility. This prompts a more systematic analysis to uncover which macroprudential policies are more useful in achieving first-best outcomes, and which policies are more useful in reducing the volatility in the economy.

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Appendix

A Fixed Parameters, Prior & Posterior Distributions of All Estimated Parameters and Estimated Moments

Table 6 provides a summary of all fixed parameters in the model, whereas Table 7 shows the posterior moments for all estimated parameters. The posterior distributions for all parameters are plotted in Figures 15 and 16.

In Table 8, we compare some model-generated moments with the empirical ones for key variables. We focus on two variables on the real side, output and wage growth rates, and two variables on the financial side, mortgage and corporate credit growth rates. In terms of standard deviations, the model matches corporate credit and wage growth rates reasonably well, while the model-generated volatility for output and mortgage growth rates is higher than the empirical ones. In terms of correlations, the model typically captures the sign. An exception is the correlation between wage and mortgage credit growth rates, which is weakly positive in the data (0.31) and weakly negative in the model (-0.09). Besides this, the strong correlation between the mortgage and credit growth rates (0.93) is not captured well in the model, which implies a weaker correlation (0.41). Overall, the model is able to match some moments consistent with the data, while there is more room to improve in terms of some moments. It is important to keep in mind that the fixed parameters, as reported in Table 6, play an important role in the model-implied moments. Hence using these parameters via e.g. a simulated method of moments could allow us to better match the empirical moments. We leave this as a potential future extension.

Parameter	Description	Value
γ	Depositor cost of bank default	0.1
β_s	Discount factor for patient households	0.995
μ_m	Bankruptcy cost of households	0.3
μ_e	Bankruptcy cost of businesses	0.3
μ_B	Bankruptcy cost of banks	0.3
α	Capital share in production	0.3
η	Frisch elasticity of labor	1
φ_s	Labor preference for patient households	1
φ_m	Labor preference for impatient households	1
a_s	Share of default costs paid by patient households	0.5
a_b	Share of default costs paid by impatient households	0.5
χ_e	Business dividend payouts	0.1
χ_b	Bank dividend payouts	0.15
v_s	Housing preference for patient households	0.25
v_m	Housing preference for impatient households	0.5
δ_H	Housing depreciation rate	0.01
δ_K	Capital depreciation rate	0.04
τ_m	Market power in the mortgage sector	40
τ_F	Market power in the corporate sector	40
ψ_b	Bank cost function hyperparameter	5
ν	Bank cost function hyperparameter	0.5
rp	Household loan repayment rate	0.01
rp_e	Corporate loan repayment rate	0.05
Policy Parameters		
$\bar{\varphi^m}$	Minimum capital requirement, mortgage sector	0.11
$\bar{\varphi^e}$	Minimum capital requirements, corporate sector	0.11
ϕ^m	Mortgage CCyB	0
ϕ^e	Corporate CCyB	0
$L\bar{T}V^m$	Household LTV	0.86
$\bar{\epsilon^e}$	Entrepreneur borrowing limit	0.86
Target Ratios		
Variable	Steady-state Ratio	Empirical Ratio
Corporate Lending to Output	133%	118%
Mortgage Lending to Output	86%	81%
investment to output ratio	12%	17%

Table 6. Fixed Parameters.

Parameter	**Prior**			**Posterior**			
	Dist	Mean	Variance	Mode	Mean	5% HPD	95% HPD
ϵ_A	Uniform	10	5.77	0.0078	0.0079	0.0068	0.0092
ϵ_J	Uniform	10	5.77	0.0971	0.1012	0.0831	0.123
ϵ_H	Uniform	10	5.77	0.0396	0.0505	0.0322	0.0778
ϵ_{Se}	Uniform	10	5.77	0.0462	0.1126	0.0328	0.3009
ϵ_{SB}	Uniform	10	5.77	0.0308	0.0318	0.0244	0.0402
ϵ_{We}	Uniform	10	5.77	0.0053	0.0055	0.0047	0.0064
ϵ_{markup_m}	Uniform	10	5.77	0.0005	0.0005	0.0004	0.0006
ϵ_{markup_e}	Uniform	10	5.77	0.0004	0.0004	0.0003	0.0004
ϵ_{EC}	Uniform	10	5.77	0.0288	0.0296	0.0253	0.0346
ϵ_{ECAB}	Uniform	10	5.77	0.0379	0.0383	0.029	0.0493
ϵ_{LTVH}	Uniform	10	5.77	0.1353	0.1593	0.1131	0.2121
ϵ_{EbF}	Uniform	10	5.77	0.0423	0.0436	0.037	0.0512
ρ_A	Beta	0.5	0.2	0.9956	0.9907	0.9786	0.9977
ρ_J	Beta	0.5	0.2	0.9849	0.984	0.9737	0.9924
ρ_H	Beta	0.5	0.2	0.9572	0.9421	0.9022	0.9726
ρ_{Se}	Beta	0.5	0.2	0.499	0.5	0.1722	0.8285
ρ_{SB}	Beta	0.5	0.2	0.0328	0.053	0.0142	0.1108
ρ_{We}	Beta	0.5	0.2	0.8434	0.8382	0.7723	0.8975
ρ_{markup_m}	Beta	0.5	0.2	0.8717	0.8694	0.7854	0.9439
ρ_{markup_e}	Beta	0.5	0.2	0.9347	0.9291	0.8842	0.9677
ρ_{EC}	Beta	0.5	0.2	0.8424	0.8436	0.8023	0.8802
ρ_{ECAB}	Beta	0.5	0.2	0.5007	0.5037	0.1742	0.8316
ρ_{EbF}	Beta	0.5	0.2	0.9268	0.9197	0.8664	0.9671
ρ_{LTVH}	Beta	0.5	0.2	0.9292	0.9067	0.8228	0.9689
ψ_i	Normal	4	1.5	7.9159	8.1069	5.7565	10.6692
ψ_h	Normal	4	1.5	4.8532	5.9162	3.507	8.7183
ζ_m	Beta	0.5	0.2	0.7179	0.7154	0.6645	0.7624
ζ_e	Beta	0.5	0.2	0.4967	0.4922	0.4293	0.5514
β_m	Beta	0.98	0.01	0.9719	-	-	-
λ	Beta	0.5	0.2	0.6626	-	-	-
σ_e	Inv. Gamma	2	0.1	0.0802	-	-	-
σ_m	Inv. Gamma	2	0.1	0.0915	-	-	-
σ_B	Inv. Gamma	2	0.1	0.0751	-	-	-

Table 7. Posterior Distributions.

	Δy_t	Δb_t^e	Δb_t^m	Δw_t
St. Dev	1.13 (0.63)	4.64 (4.09)	10.32 (5.02)	0.92 (0.9)

Correlations:

	Δb_t^e	Δb_t^m	Δw_t
Δy_t	0.31 (0.19)	0.47 (0.29)	0.17 (0.27)
Δb_t^e		0.41 (0.93)	0.16 (0.3)
Δb_t^m			-0.09 (0.31)

Table 8. Comparison of some model-based moments with the empirical moments. The first number in each cell reports the model-based moment, whereas the number in parentheses refers to the empirical moment over the estimation period.

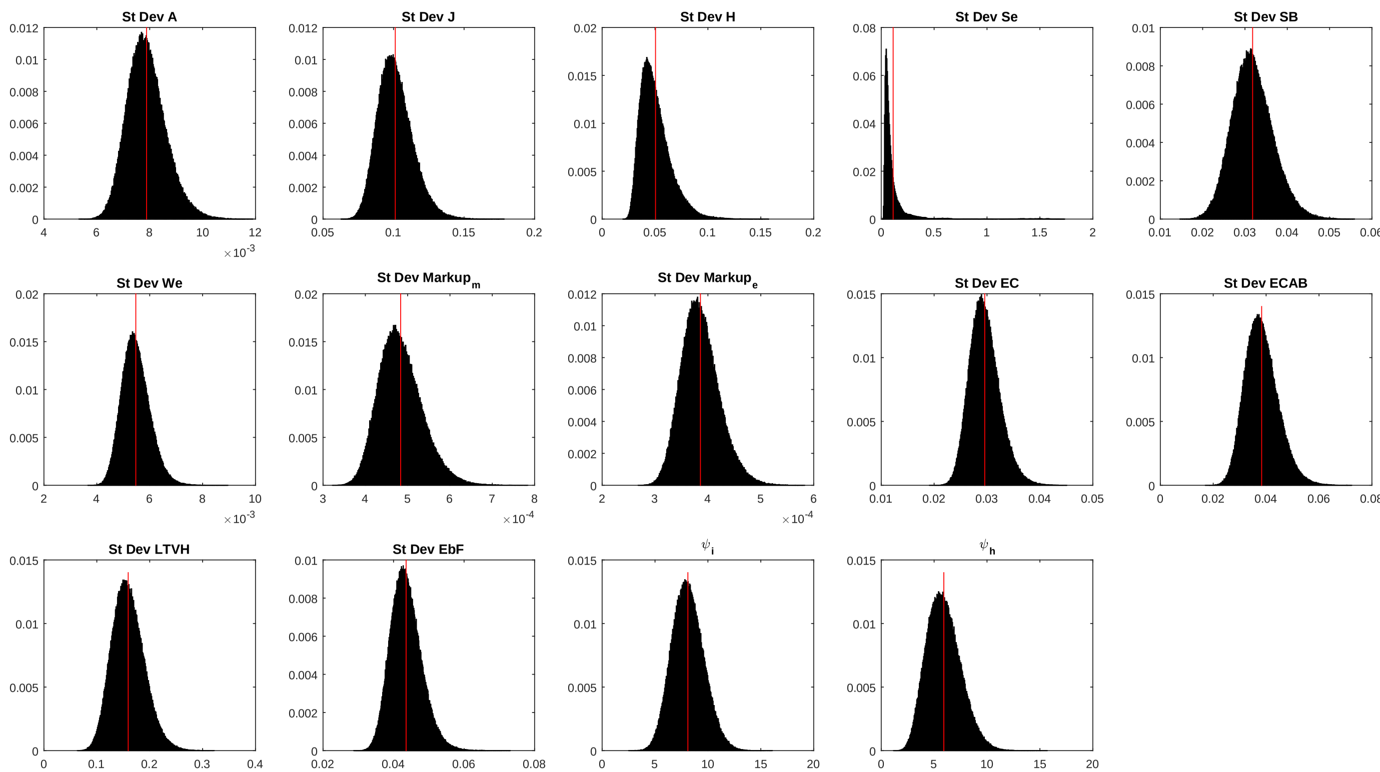

Figure 15. Posterior Parameter Distributions I.

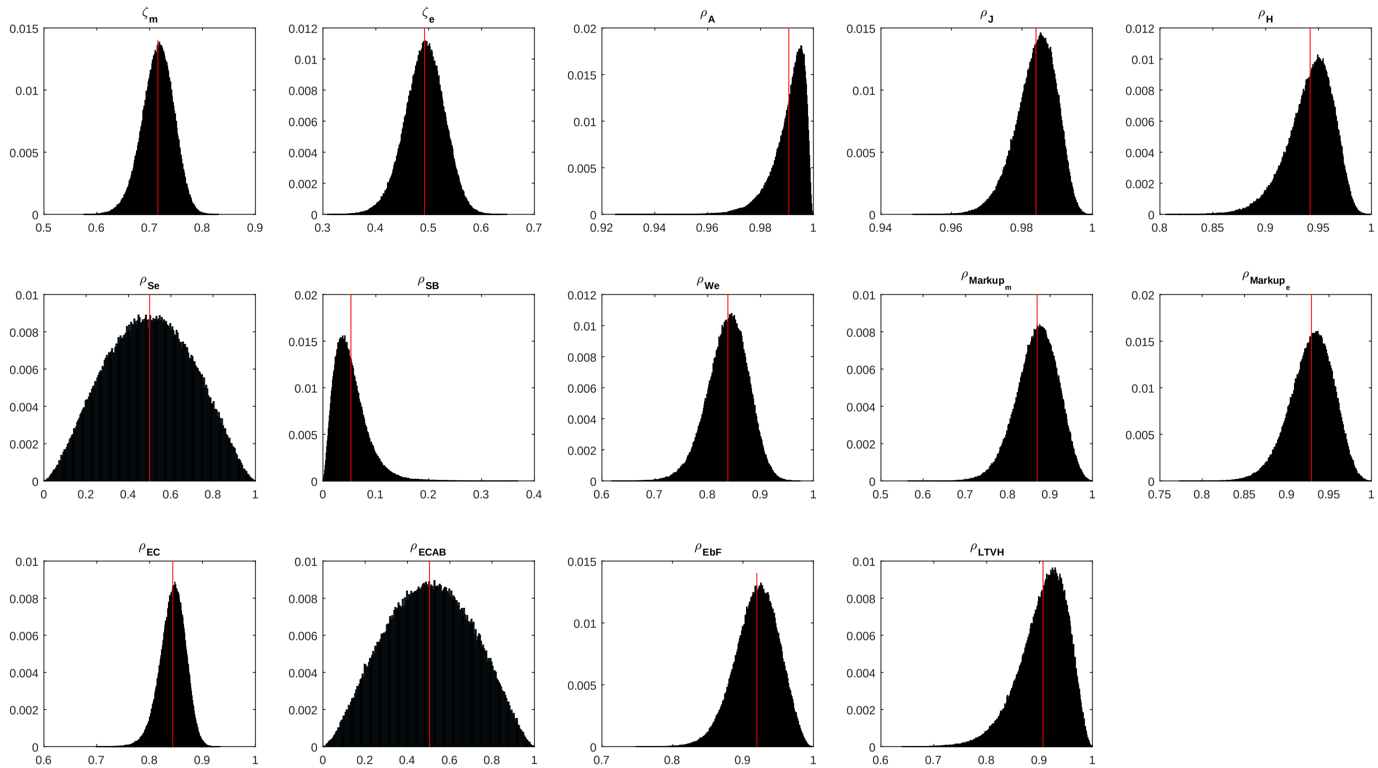

Figure 16. Posterior Parameter Distributions II.

A.1 Convergence Diagnostics

This section discusses the results of some convergence tests for the MCMCs reported in Section 3. Table 9 reports the p-values from Geweke's Convergence diagnostics (1999). The test compares the sample moments of the initial 20% and last 50% of the posterior draws. For all 8 chains, at a 5% significance level, the test fails to reject that the distribution is different at the beginning and end of the chain, indicating convergence for all chains. We also examine the CUSUM plots for each estimated parameter, as well as the Brooks & Roberts (1998) convergence diagnostics for comparing pooled and within MCMC moments (the plots for these tests are not reported here for brevity). All results indicate convergence of the chains. We further check that there is no strong correlation between the standard deviations of the estimated shocks. We observe (weak) correlation for some shock pairs, such a positive correlation between the bank capital and bank net worth shocks, or a negative correlation between the housing and consumption preference shocks, but the correlation coefficient never exceeds 20% in the reported posterior draws.

Tapering Step	4%	8%	15%
Convergence test p-values			
Chain 1	92%	93%	93%
Chain 2	69%	68%	67%
Chain 3	48%	68%	67%
Chain 4	76%	77%	76%
Chain 5	94%	95%	95%
Chain 6	86%	87%	87%
Chain 7	6%	19%	38%
Chain 8	53%	55%	55%

Table 9. Geweke's Convergence Diagnostics (1999). For all 8 MCMCs, we report p-values from tests with 3 different tapering steps, namely 4%, 8% and 15%, which takes into account the autocorrelation in the chains. After discarding the initial 20% (i.e. 50000 draws) of the sample as burn-in, the test compares the moments of the first 20% and last 50% of the posterior draws.

B Historical Series and the Estimated Shocks

Figure 17 shows the full set of estimated shocks over the sample period, whereas Figure 18 plots the time series used in the estimation. Figure 19 shows the estimated default rates for the household and banking sectors. We omit the default rate for the corporate sector which remains practically at zero throughout the sample period, implying that this layer of default does not play an important role for the model dynamics. The bank default rate somewhat increases during the crisis period, although it still remains at low levels throughout the sample. We also experimented with an alternative version of the model, where we use the average price-to-book ratio of U.K. banks as a proxy for the AR(1) bank risk shock, which directly determines the bank default rate in the model. In this case we obtain a sharper jump in the bank default rate during the crisis, but the overall default rate as well as the wider implications for the model remain qualitatively similar. Unlike the bank and corporate default rates, the household default rate increases considerably during the crisis period, and it remains elevated until 2012 before starting to come down. Together with the redistributional entrepreneur net worth shock, this increase in the default rate can be interpreted as households bearing a large part of the costs associated with the crisis in our model.

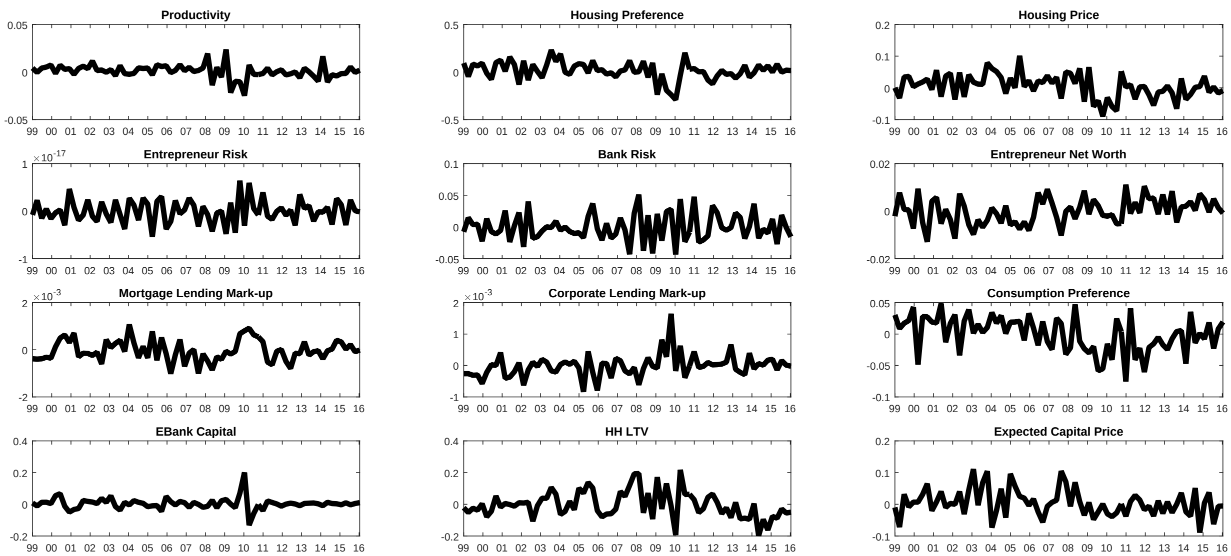

Figure 17. All estimated shocks over the sample period at the posterior mode.

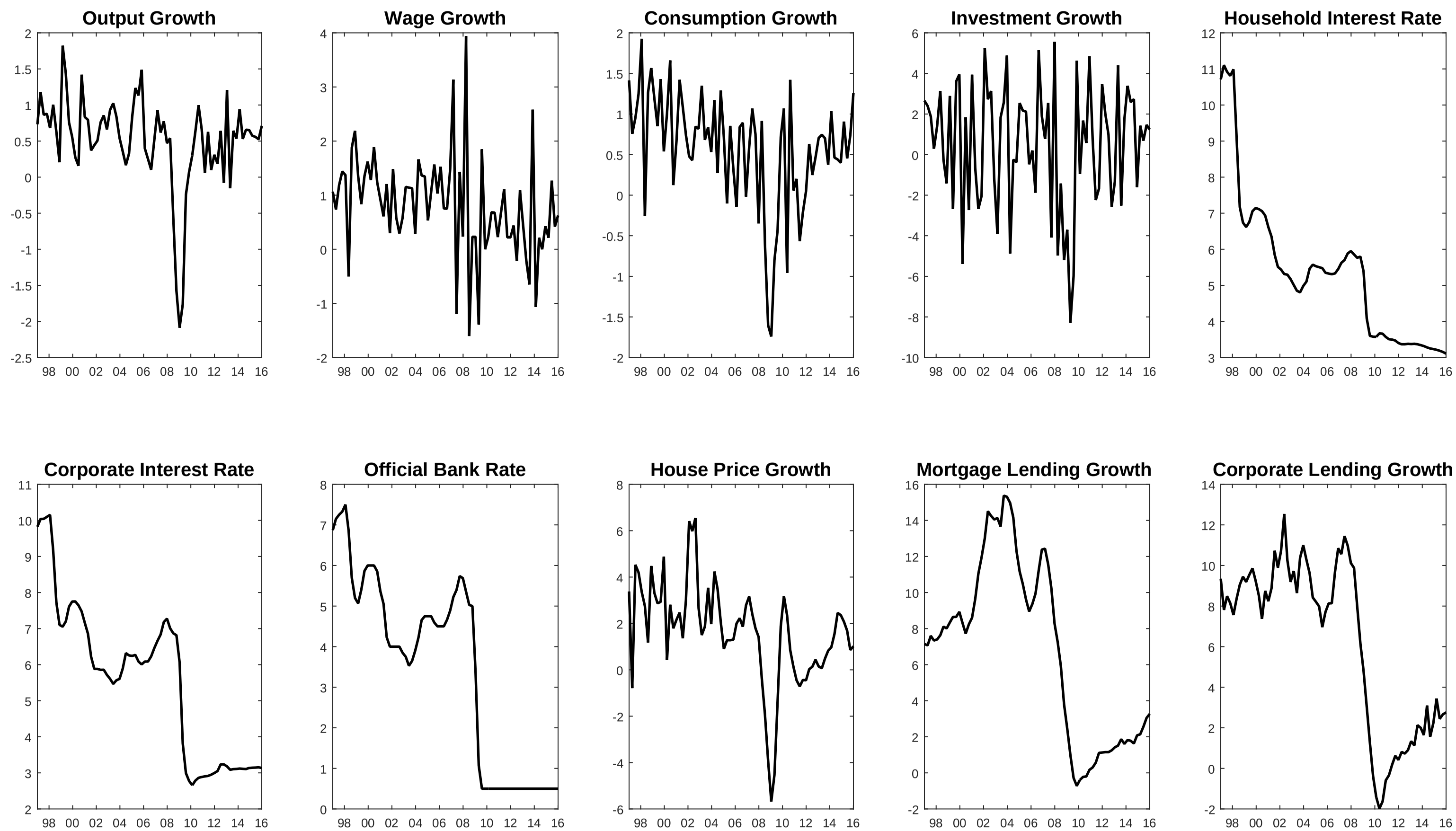

Figure 18. Observable variables used in the estimation.

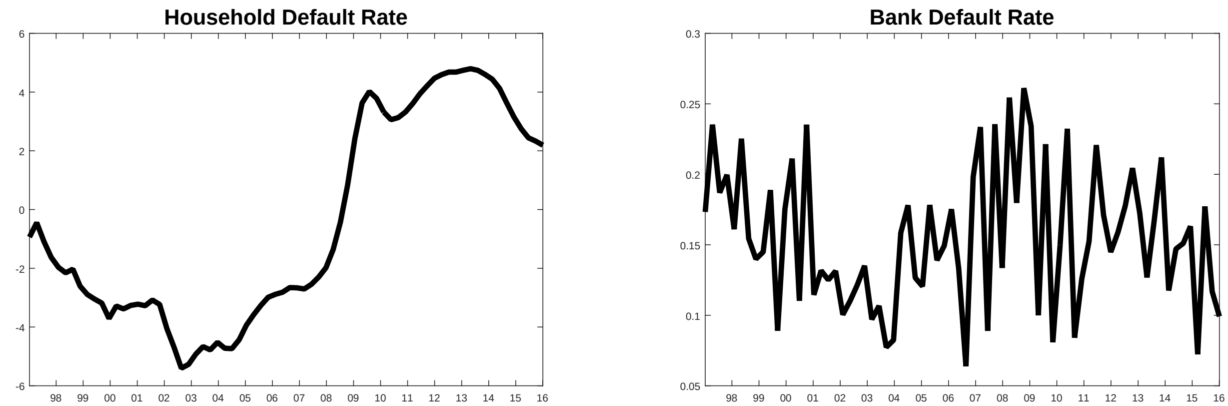

Figure 19. Default rates during the sample period, where y-axis shows the deviation in percentages from steady-state.

C Cross-country evidence on interest rate stickiness

In this section, we repeat the empirical exercise in Section 1.2 for France, Germany, Italy and Spain. We regress the monthly lending rate with 1 to 5 years of initial rate fixation on the ECB policy rate and compare this with the regression of floating interest rate loans on the ECB policy rate. We use data from the ECB Statistical Data warehouse. For the fixed rate loans, we use effective interest rate data for loans to corporations with an initial rate fixation period of over 1 to 5 years. For the floating rate loans, we use effective interest rate data for loans to corporations of over EUR 1M and an initial rate fixation period of up to one year.

In summary, we find similar results for the Eurozone countries as for the U.K. The response of the lending rate on impact (i.e. during the same month) is very small. In the case of variable interest rate loans, the bulk of adjustment takes place in the following period, whereas the adjustment in fixed rate loans is reflected over a longer period.

Regressor	France	Germany	Italy	Spain
γ_0	0.054***	0.015***	0.014**	0.0027
γ_1	0.257***	0.246***	0.258***	0.151**
γ_2	0.316***	-0.009	0.124***	0.215**
γ_3	0.294***	0.134***	0.17***	0.203**
γ_4	-0.249*	-0.04	-0.119**	-0.049
γ_5	0.366***	0.033	-0.09	-0.047**
constant	0.105***	0.035***	0.046**	0.014

Table 10. Regression of 1 to 5 year lending rate on ECB policy rate.

Regressor	France	Germany	Italy	Spain
γ_0	0.0729***	0.137***	0.034**	0.045**
γ_1	0.766***	0.481***	0.597***	0.670**
γ_2	- 0.009	0.389***	0.251***	0.203
γ_3	0.577***	0.1915	0.284***	0.466**
γ_4	-0.07	-0.157	0.049	-0.333*
γ_5	0.09	0.017	0.0165	-0.0165
constant	0.139***	0.158***	0.08**	0.153**

Table 11. Regression of floating lending rate on ECB policy rate.

For France, in response to a 1 percentage point change in the policy rate, there is about a 0.05 percentage point change in the fixed term lending rate on impact. Around 0.25 percentage point change in interest rate is passed through during the following month and around 0.3 percentage point change is passed through during the third and fourth months after the policy rate change.

For the floating interest rate loans, the response on impact is also low. However, around 76 percent of the pass-through takes place in the following month, and there is complete pass-through by the end of four months.

For Germany, in response to a 1 percentage point change in the policy rate, there is a 0.015 percentage point change in the fixed term lending rate on impact. Around 0.25 percentage point change in interest rate is passed through during the following month and around 0.13 percentage point change is passed through during the fourth month after the policy rate change.

For the floating interest rate loans, the response on impact is also low. However, around 48 percent of the pass-through takes place in the following month, and there is complete pass-through by the end of four months.

For Italy, in response to a 1 percentage point change in the policy rate, there is less than a 0.015 percentage point change in the fixed term lending rate on impact. Around 0.26 percentage point change in interest rate is passed through during the following month and around 0.12 and 0.17 percentage point change is passed through during the third month and fourth months after the policy rate change.

For the floating interest rate loans, the response on impact is also low. However, around 60 percent of the pass-through takes place in the following month, and there is complete pass-through by the end of four months.

For Spain, in response to a 1 percentage point change in the policy rate, there is less than 0.01 percentage point change in the fixed term lending rate on impact. Only around 0.15 percentage point change in interest rate is passed through during the following month and around 0.2 change is passed through during both the third month and fourth months after the policy rate change.

For the floating interest rate loans, the response on impact is also low. However, around 67 percent of the pass-through takes place in the following month, and there is complete pass-through by the end of four months.

To sum up, there is a clear pattern which emerges for all these four Eurozone economies. The response of fixed term lending rates on impact is very low. Around 25 per cent of the pass-through takes place in the following period and around 20 to 30 per cent of the pass-through takes place in the third and fourth months. Overall, the pass-through of the interest rate for fixed term loans is incomplete as observed in the U.K. data. For the floating interest rate loans, the response on impact is also low. However, around 50 to 70 percent of the pass-through takes place in the following month and there is complete pass-through by the end of four months. On the whole, we find that interest rate pass-through is fastest in France as compared to Germany where it is the slowest among these four Eurozone economies.

D Model First-order Conditions

This section provides some of the first-order conditions for the model that are omitted in Section 2 for brevity.

Patient households

In equilibrium, patient households are savers who hold deposits with the bank and buy houses with their own funds.

The objective function of the patient households (as is the case with impatient households) includes utility from consumption goods and housing and disutility from labor.

$$\max_{c_t^s, L_t^s, D_t, H_t^s} E_t \sum_{t=0}^{\infty} \beta_s^t [log(\hat{c_t^s}) + vlog(H_t^s) - \frac{(L_t^s)^{1+\eta}}{1+\eta}]. \tag{D.1}$$

This is subject to the following budget constraint:

$$c_t^s + q_t^H H_t^s + D_t = w_t L_t^s + q_t^H H_{t-1}^s (1-\delta) + D_{t-1} R_t^D + \pi_t. \tag{D.2}$$

The term π_t includes profits of final goods producing firms and investment/housing production firms (which are owned by patient households), dividends from entrepreneurs and lump-sum transfers from the deposit insurance agency.

The FOCs for deposits and the housing stock are given by:

$$U'(\hat{c_t^s}) = \beta_s E_t[U'(\hat{c_{t+1}^s}) R_{Dt}], \tag{D.3}$$

$$U'(\hat{c_t^s}) q^H = E_t[\beta_s U'(H_{t+1}^s) + \beta_s U'(\hat{c_{t+1}^s})(1-\delta) q_{t+1}^H]. \tag{D.4}$$

Impatient households

Impatient households borrow from banks using their houses as collateral as in Bernanke et al. (1999). These mortgage loans are made on a limited liability non-recourse basis, implying that individual households default whenever the value of the house is lower than the outstanding mortgage loans. The value of the house depends both on aggregate shocks (which affect house prices) as well as an idiosyncratic shock which determines whether an individual borrower defaults. In equilibrium, borrowers with an idiosyncratic shock below a certain threshold default. In the case of default, the bank takes possession of the houses in which case it is subject to state verification costs.

The borrowing is subject to an LTV (loan-to-value) limit set by the regulator. It is similar to a borrowing/collateral constraint as in Kiyotaki & Moore (1997).

The objective function of the impatient households is the same as that of the patient households except for the discounting factor:

$$\max_{c_t^m, B_t^m, L_t, H_t^m} E_t \sum_{t=0}^{\infty} \beta_m^t [log(\hat{c_t^m}) + vlog(H_t^m) - \frac{(L_t^m)^{1+\eta}}{1+\eta}]. \tag{D.5}$$

The budget constraint of impatient households reflects their borrowings under limited liability:

$$c_t^m + q_t^H H_t^m - B_t^m = w_t L_t^m + \int_{\bar{\omega_t^m}}^{\infty} \left(\omega_t^m q_t^H H_{t-1}^m (1-\delta) B_{t-1}^m R_{t-1}\right) \, dF\omega_t^m + P_t. \tag{D.6}$$

The term under the integral reflects the limited liability of the borrowers as they default on their loans when the idiosyncratic shock ω_t^m is below the threshold level of $\bar{\omega^m}_t$.

The default decision by the borrowers is given by:

$$\omega_t^m q_t^H H_{t-1}^m (1-\delta) \leq B_{t-1}^m R_{t-1}^m. \tag{D.7}$$

The threshold level of $\bar{\omega^m}_t$ satisfies:

$$\bar{\omega^m}_t q_t^H H_{t-1}^m (1-\delta) = B_{t-1}^m R_{t-1}^m \tag{D.8}$$

The LTV limit (or the borrowing constraint) is given by:

$$[B_t^m - (1-rp)B_{t-1}^m] R_t \leq \epsilon_t^m E_t[q_{t+1}^H [H_t^m - H_{t-1}^m (1-\delta)]], \tag{D.9}$$

where rp is the loan repayment rate and ϵ_t^m is the LTV limit. The limit always binds in the steady state and its neighborhood. The FOCs for mortgage loans and the housing stock are given by:

$$E_t U'(\hat{c_t^s}) - \beta_m U'(\hat{c_{t+1}^s})(R_t^m(1-def_{t+1})) - \lambda_t R_t^m + \lambda_{t+1}(1-rp)(1-def_{t+1})R_{t+1}^m = 0, \tag{D.10}$$

$$U'(\hat{c_t^s}) q^H = \beta_m U'(H_{t+1}^s) + \beta_s U'(\hat{c_{t+1}^s})(1-Gm_{t+1})(1-\delta) q_{t+1}^H + \lambda_t(\epsilon_t q_{t+1}^H) - \lambda_{t+1}(\epsilon_{t+1} q_{t+2}^H)(1-\delta), \tag{D.11}$$

where $def()$ is the probability of default and the function $Gm()$ represents the proportion of housing stock taken over by the bank for defaulted loans. λ_t is the Lagrange multiplier on the LTV constraint.

Capital goods and housing production

Firms are competitive, buy finished goods and produce capital goods / housing subject to quadratic adjustment costs. Firms produce new units of capital and housing using consumption goods which are then sold to entrepreneurs and households, respectively, at prices q^K and q^H. They represent the supply side of the capital goods / housing sectors and pin down the equilibrium asset prices. Firms are owned by the patient households.

They maximise their profits as follows:

$$\max_{I_t} E_t \sum_{i=0}^{\infty} \beta_s^t \{ \frac{c_t^s}{c_{t+1}^s} \} [q_{t+i}^K I_{t+i} - \{1 + g[\frac{I_{t+i}}{I_{t+i-1}}]\}] \tag{D.12}$$

$$\max_{I_t^H} E_t \sum_{i=0}^{\infty} \beta_s^t \{ \frac{c_t^s}{c_{t+1}^s} \} [q_{t+i}^H I_{t+i} - \{1 + g[\frac{I_{t+i}^H}{I_{t+i-1}^H}]\}] \tag{D.13}$$

E Objective Function Calculations

This Appendix provides details on the optimal policy calculations reported in Section 4. In order to calculate the individual optimal policies in Table 3, we use a grid search as follows: for each policy tool, we specify a grid length of 100. For housing LTV, we consider the range over $[0.7, 0.95]$. For SCRs and CARs, this range is given by $[0.05, 0.25]$.

Recall that the CAR, i.e. the minimum capital requirement for the bank, is implicitly determined as the minimum of the two sectoral capital requirements:

$$\varphi_t = min\{\varphi_t^m, \varphi_t^e\},$$

with φ_t the capital adequecy ratio and φ_t^m, φ_t^e the sectoral capital requirements. Therefore, when computing the optimal CAR in our analysis, we impose the restriction $\varphi_t^m = \varphi_t^e$. Hence, this is equivalent to a scenario where both sectoral capital requirements remain at the same level (i.e. there are no sector-specific add-ons). When calculating the optimal SCRs, each sectoral requirement is varied over the indicated range while the other requirement is fixed at the benchmark value of 0.11.

For the joint optimisation of policy tools reported in Table 4, note that we effectively maximise over three policies, i.e. LTV and two SCRs. The CAR is then implicitly determined as the minimum of the two SCRs as discussed above. For this exercise, since the dimension of the objective function is larger (compared to the 1-dimensional case), we use a smaller grid length of 20 to keep the computational cost at a minimum. While we use the same parameter ranges as in the individual maximisation exercise, some combinations of SCRs and LTVs lead to indeterminacy in this case. Such combinations are discarded during the calculations.

Households' weights in the welfare objective are based on Mendicino et al. (2018). It is important to stress that this weighting function does not account for potential implications with respect to inequality. For example, our results in Figure 7 show that, while the total welfare clearly increases in the counterfactual experiment, most of the improvement comes from savers' welfare. In this paper, we abstract away from inequality implications, which has been analysed in other papers such as Mendicino et al. (2018).

An alternative version of the welfare objective with weights based on households' population shares (fixed at 0.5) yields qualitatively similar results compared to the reported values in Section 4, suggesting that our conclusions are robust to such changes.