Financial imbalances and macroeconomic tail risks: A structural regime-switching investigation

This paper examines how excessive credit growth and asset price overvaluation increase the likelihood of financial crises and deepen associated economic downturns, and assesses the implications for monetary and macroprudential policies

Yasin Mimir
European Stability Mechanism

Lorenzo Ricci
European Stability Mechanism

European Stability Mechanism

Financial imbalances and macroeconomic tail risks: A structural regime-switching investigation

Yasin Mimir [1] European Stability Mechanism

Lorenzo Ricci [2] European Stability Mechanism

Abstract

We first empirically document that excessive credit growth and asset price overvaluations raise the likelihood of financial crises and deepen the severity of associated economic downturns in advanced economies using linear probability models and local projections. We then rationalise these empirical findings in a Markov regime-switching version of a canonical New Keynesian DSGE model with the banking and housing sectors estimated for the euro area, which explicitly accounts for prolonged financial cycles based on hybrid house-price expectations and the nonlinearities arising from financial imbalances. The model offers a framework in which low-probability financial crashes are nested within typical business cycles. We then present several policy applications to show how this framework can be used to conduct structural macro-financial risk analysis depending on the evolution of financial conditions and to assess monetary and macroprudential policies, uncovering key policy trade-offs.

Keywords: Regime-switching models, financial imbalances, macroprudential policy, financial stability

JEL codes: C53, E12, E50, E30, G01

[1] y.mimir@esm.europa.eu

[2] l.ricci@esm.europa.eu

ISSN 2443-5503
doi: 10.2852/ 9143438
ISBN 978-92-95223-58-5
EU catalog number: DW-01-24-003-EN-N

Financial imbalances and macroeconomic tail risks: A structural regime-switching investigation *

By Yasin Mimir and Lorenzo Ricci †

We first empirically document that excessive credit growth and asset price overvaluations raise the likelihood of financial crises and deepen the severity of associated economic downturns in advanced economies using linear probability models and local projections. We then rationalise these empirical findings in a Markov regime-switching version of a canonical New Keynesian DSGE model with the banking and housing sectors estimated for the euro area, which explicitly accounts for prolonged financial cycles based on hybrid house-price expectations and the nonlinearities arising from financial imbalances. The model offers a framework in which low-probability financial crashes are nested within typical business cycles. We then present several policy applications to show how this framework can be used to conduct structural macro-financial risk analysis depending on the evolution of financial conditions and to assess monetary and macroprudential policies, uncovering key policy trade-offs.

JEL: C53, E12, E50, E30, G01
Keywords: Regime-switching models, financial imbalances, macroprudential policy, financial stability

I. Introduction

A long history of financial crises in advanced economies, including the 2007-09 global financial turmoil, shows that these events tend to be preceded by excessive growth in real private credit and overvaluation of asset prices and are usually followed by more severe economic downturns that are significantly different from typical recessions (Jordà, Schularick and Taylor, 2013, 2016). Credit imbalances coupled with overvalued house prices along with long-lasting financial cycles are key to explaining these events (Claessens, Kose and Terrones, 2012; Drehmann, Borio and Tsatsaronis, 2012; Claessens et al., 2013).

Generating financial crises nested within typical business cycles proves to be difficult for a wide range of macroeconomic models, including the most recent New Keynesian DSGE models with financial frictions (Mendoza, 2010). These models

* We thank the seminar participants at the European Stability Mechanism (ESM) and 4th Sailing the Macro Workshop.

† Mimir: European Stability Mechanism (ESM), 6a Circuit de la Foire Internationale, L-1347 Luxembourg, y.mimir@esm.europa.eu. Ricci: European Stability Mechanism (ESM), 6a Circuit de la Foire Internationale, L-1347 Luxembourg, l.ricci@esm.europea.eu.

generally fall short of capturing simultaneously the following four key characteristics of boom-bust episodes observed in advanced economies. First, financial cycles are more prolonged than business cycles (Claessens, Kose and Terrones, 2012; Claessens et al., 2013; Drehmann, Borio and Tsatsaronis, 2012). Household debt and house prices are more persistent than standard macro variables like output, and expectations about house prices play a crucial role in driving prolonged financial cycles (Gelain, Lansing and Mendicino, 2013). Second, financial crises are rare events nested within typical business cycles. Third, these events come across as asymmetric and nonlinear, with long-lasting effects on the macroeconomy. Finally, they are mainly triggered by accumulated financial imbalances in credit and asset prices over time. Therefore, loose financial conditions in normal times are linked to future downside risks to GDP (Adrian, Boyarchenko and Giannone, 2019).

While there are many attempts in the literature to incorporate financial factors and crises into macroeconomic models, an empirically-disciplined and unified structural framework that could explain the aforementioned nonlinear links between so-called financial imbalances, the likelihood of financial turmoil and the resulting severity of economic downturns, and their policy implications is still scarce.[1] We aim to fill this gap in the literature.

In this paper, we rationalise the key empirical regularities of financial crises in advanced economies in a Markov regime-switching version of a canonical New Keynesian DSGE model with the banking and housing sectors, which explicitly accounts for prolonged financial cycles and the nonlinearities arising from financial imbalances. Notably, the framework is designed to serve as a laboratory for conducting structural macro-financial risk analysis based on the evolution of financial conditions and for assessing monetary and macroprudential policies.

Our contribution to the literature is threefold. First, we present an endogenous Markov-regime switching (RS) version of an estimated DSGE model for the euro area with explicit modeling of the banking and housing sectors. In this framework, financial crises are endogenously triggered by the evolution of real private credit, house and equity prices, and interest rates as in the actual data. To this end, we estimate a logit specification covering 21 advanced economies from Q1-2001 to Q4-2019 (Anundsen et al., 2016), and we embed this logit specification into our RS-DSGE model to govern transition probabilities from normal times to crisis times (Gerdrup et al., 2017; Kravik, Kockerols and Mimir, 2023). This helps the model explain the observed frequency of financial crises as in the data.[2]

Second, we incorporate a reduced-form empirical function relating private credit

[1]We would like to clarify the definition of financial imbalances early on, given the motivation of the paper. Within our modeling framework, we proxy "financial imbalances" by long-term (3-year or 5-year) average growth rates of real house prices, real private credit, real equity prices, and real interest rates.

[2]Since the number of financial crises arising from the private sector financial imbalances in the euro area in our sample period from 1999 to 2019 is quite limited and the identification becomes extremely difficult, we do not attempt to estimate the RS-DSGE version of the model with Bayesian techniques. Instead, we first estimate the constant parameter version of the model for the euro area and then integrate the estimated probability of the crisis function into the model.

growth to crisis severity that is motivated by the estimated local projections (Jordà, Schularick and Taylor, 2016). This helps us capture that higher pre-crisis credit growth leads to more severe output declines. In particular, a one-standard deviation increase in pre-crisis real credit growth leads to a nearly 2% higher reduction in real GDP. We integrate this feature into our model using state-dependent heteroskedastic structural shocks conditional on accumulated pre-crisis real private credit growth, calibrated based on the estimated local projections, and regime-switching structural *dynamic* parameters governing specific elasticities and adjustment costs following Hubrich and Tetlow (2015).[3] They argue that both asymmetrically large shocks due to *variance switching* and nonlinear dynamics due to *coefficient switching* during financial distress episodes are key to explaining the behaviour of the macroeconomy during financial crises. This setup, together with endogenous transition probabilities in a Markov regime-switching framework, allows us to construct the conditional time-varying distributions of a large set of macro-financial variables, including GDP growth emphasised by the growth at risk (GaR) literature introduced by Adrian, Boyarchenko and Giannone (2019).

Third, the model can explain empirically plausible persistent financial cycles via partly backward-looking house price expectations, deviating from model-consistent rational expectations about house prices (Gelain, Lansing and Mendicino, 2013; Kravik, Kockerols and Mimir, 2023). If households observe that house prices have been rising in the past, they project that house prices will continue increasing while forming their expectations, leading to prolonged cycles in house prices and household debt in the model.

Our quantitative analysis shows that the model explains the key stylized facts of financial crises in advanced economies while still matching the typical business cycle moments in the data and preserving the frequency of normal times and crisis episodes as in the actual data. Therefore, this framework offers an empirically plausible environment to conduct structural macro-financial risk analysis, including different risk scenarios typically constructed at policy institutions.[4] After establishing the credibility of this quantitative framework, we conduct several policy applications that show how to assess the macroeconomic implications of and the trade-offs associated with different monetary and macroprudential policy trajectories, including bank capital requirements and leaning-against-the-wind (LAW)-type monetary policy rules.

[3]We document that the main macroeconomic and financial ratios in the data remain virtually the same across normal and crisis times. That is why we resort to a cyclical explanation of financial crises by using conditionally heteroskedastic shocks, which are coupled with the standard financial accelerator mechanism (Kiyotaki and Moore, 1997; Bernanke, Gertler and Gilchrist, 1999), instead of occasionally binding financial constraints, which could lead to different steady-state "great" ratios in a financial crisis regime, not supported by the data. The particular selection of conditionally heteroskedastic structural shocks is based on the crisis narrative inspired by our empirical analysis. However, our modelling framework is flexible enough to accommodate different contingencies given the potentially different nature of financial crises.

[4]The model is also able to explain zero lower-bound episodes. More formally, the effective lower bound (ELB) on the policy rate binds endogenously whenever the implied policy rate falls below the ELB, governed by a separate Markov process.

Focusing on the episode around the Global Financial Crisis (GFC) from the end of 2003 to the end of 2011, among many other exercises, we first analyse how overoptimism in house prices by economic agents prior to the GFC could have amplified the boom period and the subsequent bust episode. We then assess the potential policy complementarities between monetary and macroprudential policies around the GFC. If capital requirements had been higher before the crisis, monetary policy would not have needed to be as restrictive as in the baseline, as both the rise in inflation and output would have been less pronounced. Therefore, monetary policy could have focused on maintaining price stability while macroprudential policy could have helped to contain financial stability risks. On the other hand, if we compare implementing higher capital requirements with conducting LAW-type monetary policy before the GFC, we find that although the costs of implementing these two policies are comparable in terms of output loss before the crisis, the crisis is less severe and the recovery is much faster in the case of using higher capital requirements.

Related literature This paper is closely related to two strands of the literature that study the role of financial factors, especially private credit and asset prices, in explaining the dynamics of financial crises in advanced economies. On the empirical front, Jordà, Schularick and Taylor (2013) and Jordà, Schularick and Taylor (2016) document that financial recessions are more costly than normal recessions in terms of lost output. For both types of recessions, more credit-intensive expansions tend to be followed by deeper economic downturns and slower recoveries. They also show how past credit accumulation impacts output behaviour and other key macroeconomic variables such as investment, lending, interest rates, and inflation. We contribute to this strand of empirical literature by confirming their results for advanced economies and estimating logistical regressions for the probability of financial crises in these countries by including more financial variables.

Our paper also contributes to the theoretical literature that explains financial crises in advanced economies and sudden stops in emerging economies using occasionally binding financial constraints (Mendoza (2010) and Benigno et al. (2021)). Our paper differs from the latter as we focus on financial crises in major developed countries while Mendoza (2010) and Benigno et al. (2021) focus on sudden stops in emerging markets. Moreover, the probability of a crisis is explicit in our framework as we rely on empirically estimated logit specification using real private credit, real house and equity prices and real interest rates, while the probability of a sudden stop in Mendoza (2010) and Benigno et al. (2021) depends on the likelihood of a binding collateral constraint. Finally, we are able to solve a fairly large-scale New Keynesian DSGE model with the housing and banking sectors using Markov regime-switching techniques while explaining many salient features of the boom-bust episodes in advanced economies such as prolonged financial cycles and higher severity of crises depending on pre-crisis private credit growth. In that regard, Adrian, Gaspar and Vitek (2024) also builds a large-scale open economy DSGE model with macro-financial linkages and endogenous risk based on Adrian, Boyarchenko and Giannone (2019) to analyse different policy instruments in advanced and emerging market economies. Our paper differs from their setup of endogenous risk. In particular, we rely on a Markov regime-switching DSGE model with explicit endogenous transition probability that governs moving from normal times to crisis state based on an estimated logit specification, and regime-switching dynamic structural parameters and state-dependent heteroskedastic structural shocks conditional on accumulated pre-crisis real private credit growth, calibrated based on the estimated local projections. On the other hand, their framework incorporates conditional variances into structural shocks based on output and financial gap measures depending on whether the shock is macroeconomic or financial in a constant-parameter DSGE model.

The rest of the paper proceeds as follows. Section II shows the key stylised facts about financial crisis episodes in advanced economies. Section III describes the theoretical model consistent with these empirical regularities. Section IV presents the calibration and estimation of the model. Section V discusses the quantitative findings for the euro area, and policy simulations are shown in Section VI. Finally, Section VII concludes.

II. Diagnostics of Financial Crises in Advanced Economies

This section discusses the selection of various financial indicators and their behaviour around financial crises. Our panel dataset contains quarterly data for 21 OECD countries from 1975 through 2019. Our sample includes Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Japan, Korea, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.[5] We identify the episodes of financial crisis relying mainly on the crisis classifications suggested by Lo Duca et al. (2017) and (Laeven and Valencia, 2020, 2013).[6] Comparable to Anundsen et al. (2016), we identify 31 episodes in the pooled panel data set as financial crises.

Our choice of financial indicators is guided to a large extent by the empirical and theoretical literature on measuring risks in the financial system. We use a set of indicators covering credit and asset price developments. The empirical literature has identified credit and asset prices (i.e., real estate prices) as key financial cycle drivers (Drehmann and Juselius, 2012). They perform robustly in signaling financial crises in studies using international data. Several papers have focused on the co-movement of medium-term cycles in credit and property prices as the defining characteristics of the financial cycle (Claessens, Kose and Terrones, 2012; Aikman, Haldane and Nelson, 2015). They also find that cycles in financial variables tend to be distinct from business cycles, with lower frequency, and that

[5] Table A.3 in the appendix contains summary statistics for relevant data.

[6] We also verify our episodes with the ones described on Reinhart and Rogoff (2008, 2009*a*,*b*) and Babecky̌ et al. (2014).

financial cycle peaks are closely associated with financial crises and, hence, low economic growth.

Many studies conducted since the Global Financial Crisis found credit booms as the major predictor (Schularick and Taylor, 2012; Dell'Ariccia et al., 2012). According to Jordà, Schularick and Taylor (2013), financial crises preceded by credit booms are also more costly than other crises, implying a strong link between credit booms and the likelihood of a severe crisis. Drehmann, Borio and Tsatsaronis (2011) and Drehmann and Tsatsaronis (2014) also proposed an essential role for credit indicators in anchoring countercyclical capital buffers, building on earlier studies on banking crises (Borio, Lowe et al., 2002; **?**). We consider real total credit as a financial indicator due to credit's fundamental significance in the empirical literature on financial crises.[7]

Housing accounts for a significant portion of household wealth in many nations and its importance as collateral makes it relevant in analysing financial system vulnerabilities. Because housing prices and credit are so closely related, self-reinforcing spirals can form, in which higher house prices lead to more lending, which leads to higher house prices yet again. Anundsen et al. (2016) discovered that bubble-like behaviour significantly affects housing and credit markets, particularly when it coincides with high household leverage. As a result, we add house prices to income as an indicator in our research.

Finally, the equity and bond markets are essential for firms seeking capital. High asset valuations and low-interest rate spreads can be indicators of rising risk appetite in specific markets. Elevated valuations in equity and bond markets can also result in a severe correction later, posing a market risk for financial institutions (Claessens, Kose and Terrones, 2012; Mendoza, 2010). We employ real equity prices (because of their more extended time series) to capture risk appetite and asset valuations. Finally, we also use interest rates to measure the soundness of the financial system (Gilchrist, Yankov and Zakrajšek, 2009; Gilchrist and Zakrajšek, 2012; Hubrich and Tetlow, 2015; Fink and Schüler, 2015).

What proportion of these financial crisis episodes was associated with heightened imbalances, as measured by our metrics introduced above? Table 1 provides an overview of these events, indicating that a significant portion (equal or more than 50%) of these events is associated with large financial imbalances at the beginning of the crisis. In our sample, more than 90% of these crises were preceded by high credit growth, defined by 5-year growth in credit above its country-specific mean at the onset of the crisis. This estimate is close to the finding in

[7]Several publications have emphasised the rapid increase in household debt in the United States as a critical mechanism for understanding the sluggish macroeconomic recovery since then (Eggertsson and Krugman, 2012; Mian, Rao and Sufi, 2013). Anundsen et al. (2016) discovered that loan expansions to households and non-financial firms are significant when assessing the financial system's stability. As a result, we also use the credit to non-financial enterprises and households. Drehmann and Juselius (2012) find that debt service costs play a key role as an early-warning indicator (particularly in the short term), emphasising that when debt service costs are high, even little shocks to income or interest rates can lead to increased macroeconomic volatility. As a result, we also test for the debt service ratio of families as a financial variable.

Dell'Ariccia et al. (2016) that two credit booms in three are followed by either full-blown banking crises or extended periods of sub-par growth.[8] Similarly, a surge in house prices, defined by 5-year house prices to income, large piling up in the real return on equity, or a significant increase in real interest rate are also associated with around 80% of the financial crisis episodes identified.

We also identify how many large GDP shortfall episodes are associated with heightened financial imbalances in our sample. To define GDP shortfall, we use the annualised average growth in real GDP over a three-year horizon ($\frac{y_{i,t+12}-y_{i,t}}{3\times y_{i,t}}$) to capture persistent declines in growth.[9] Our sample of large GDP shortfall events captures the lower percentiles of the growth distribution, explicitly representing the bottom 10% of observations. Like Aikman et al. (2019), we identify that more than half of large GDP shortfall events are associated with high financial imbalances.[10]

Table 1—: Financial imbalances measures and financial crisis

	No. of financial crisis associated with	Average financial imbalances pre-crisis
Real credit (5Y av. growth) $> \mu_i$	96% (27 of 28)	9.4
Real house prices to income (5Y av. growth) $> \mu_i$	79% (22 of 28)	4.0
Real return on equity (3Y av. growth) $> \mu_i$	50% (14 of 28)	10.4
Real interest rate (3Y change) $> \mu_i$	82% (23 of 28)	0.7

Notes: This table presents summary statistics of the correlations between the financial crisis identified within our dataset and imbalances indicators that exceed the country average, μ_i. The average financial imbalances are computed by using annualised average growth over a three-year horizon ($\frac{z_{i,t+12}-z_{i,t}}{3\times z_{i,t}}$) or five-year horizon ($\frac{z_{i,t+12}-z_{i,t}}{5\times z_{i,t}}$).

A. *Behaviour of our financial indicators around the financial crisis episodes*

To identify the behaviour of financial indicators around the financial crisis event, we estimate a linear regression model in equation (1) following Gourinchas and Obstfeld (2012) to determine how a financial indicator's conditional expectation depends on the temporal distance from the start of the financial crisis:

$$x_{j,i,t} = \alpha_{j,i} + \beta_{j,s}\lambda_{j,i,s} + \varepsilon_{j,i,t}. \tag{1}$$

In equation (1), we estimate the expected mean ($\beta_{j,s}$) of a set of variables of interest, such as credit growth and house prices, as a deviation from its mean in "normal times" in the four years preceding and the four years following the financial crisis event. $x_{j,i,t} \in x_{i,t}$, denotes the variable of interest j, in country

[8] We also find events comparable to the financial crises described in Anundsen et al. (2016)

[9] We exclude observations less than two years apart to avoid clustering at the country level.

[10] We find 48 episodes in the pooled panel data set as large GDP shortfalls. In the appendix, Table A.4 shows the summary statistics.

i and at time t. $\lambda_{j,i,s}$ is a dummy variable taking the value one when $x_{j,i,t}$ is s quarters away from a tail event, and the value zero otherwise. The parameter $\alpha_{j,i}$ is a country fixed effect and $\varepsilon_{j,i,t}$ is an error term ($\varepsilon_{j,i,t} \sim IIN(0, \sigma^2_{x_j})$).

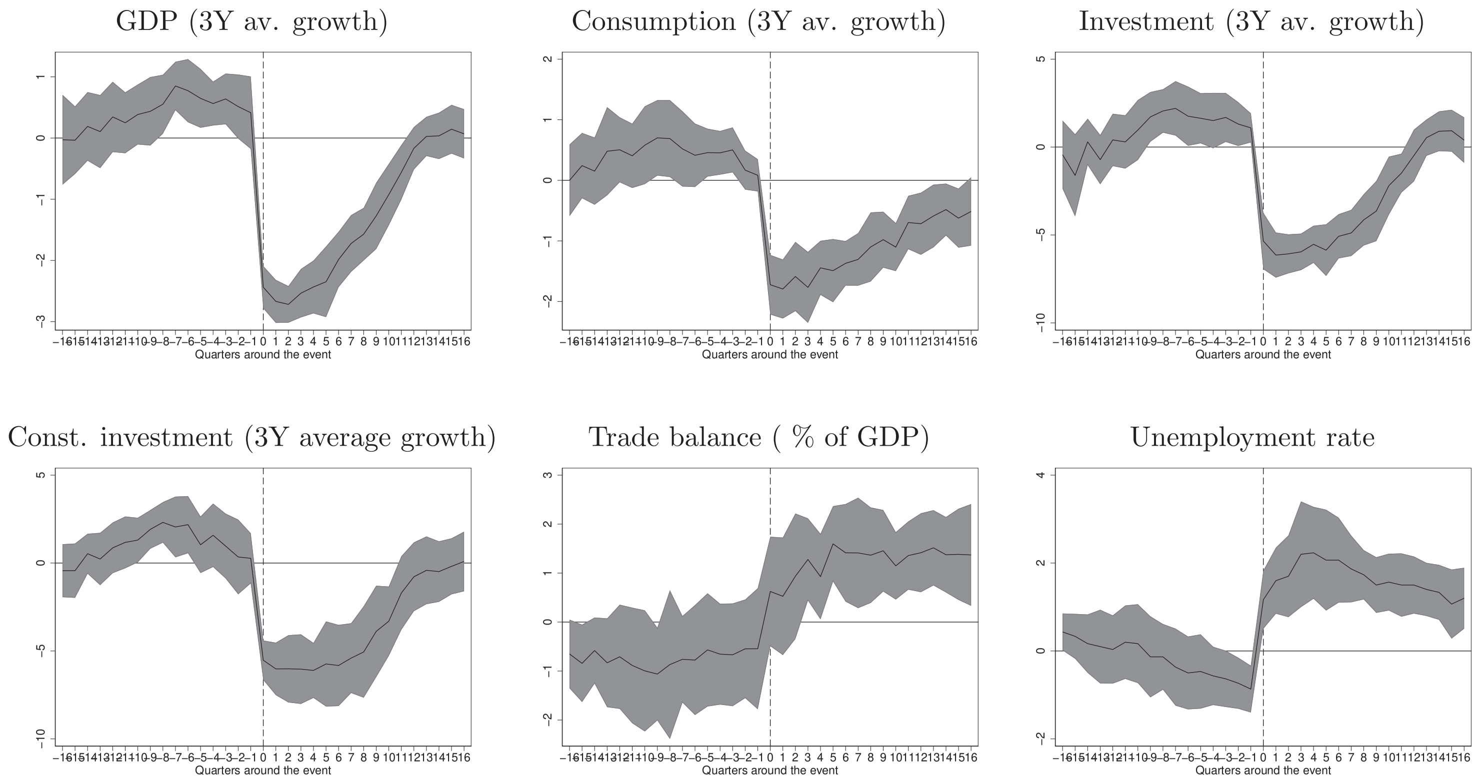
Figures 1 and 2 depict the dynamic of our macroeconomic and financial indicators around the event (i.e. estimated $\beta_{j,s}$ for various s), as well as our left-hand side measurements of GDP growth.

Fact 1. *Financial turmoils are associated with a sharp and persistent drop in economic activity.* On average GDP falls about 3% below the trend, consumption drops about 2% below the trend and investment fall around 6% (Figure 1). Net exports jump about one percentage point of GDP during the two quarters before the event and afterward. Unemployment rises by two percentage points around the tail event and remains persistently high for about two years after the event. These findings align with Yeyati and Panizza (2011) and Mendoza and Yue (2012), showing that the crisis coincides with large GDP drops in data.

Fact 2. *Real equity returns, house prices, and interest rate peak relatively early before the financial crisis.* Real equity jumps almost 5 percentage points and then drops significantly by 15 % around the event as economic conditions deteriorate. Similarly, house prices peak up 2% above the trend 12 quarters before the event, followed by a sharp and persistent decline even after six quarters of the event up to 4%. The real interest rate rises early, peaking ten quarters earlier than the tail event, followed by a sharp drop.

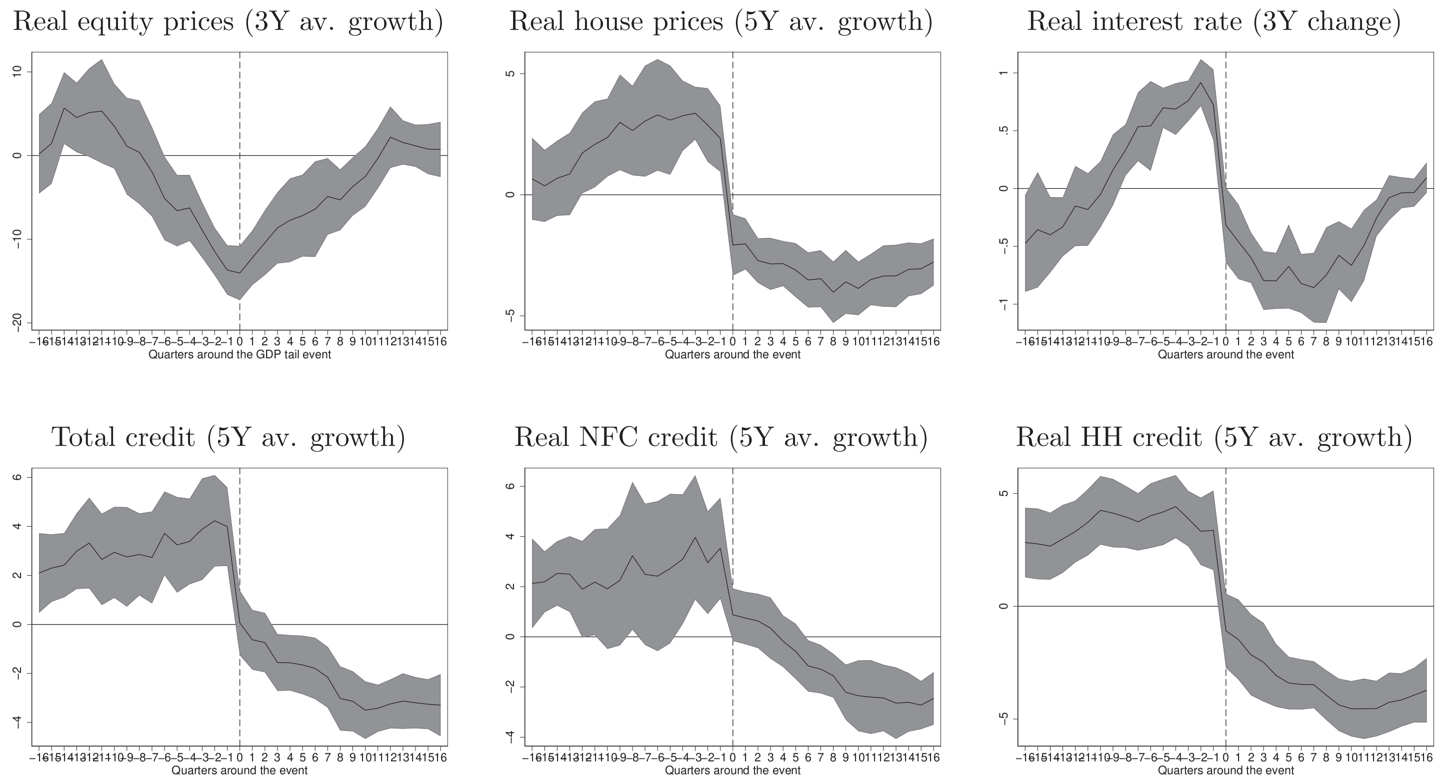
Fact 3. *Indicators based on credit peak somewhat later but before the financial crisis.* The credit-to-GDP ratio peaks closer to the event, about six quarters before. Our results suggest that financial indicators have good signaling properties and can play a relevant role in financial crises.

Figure 1. : Behaviour of financial and economic conditions around financial crises



Notes: Figures show the results from the following fixed effect panel specification on 21 advanced economies: $y_{it} = \alpha_i + \beta_{ds}\delta_{ds} + \varepsilon_{it}$, where δ_{is} denotes dummy variable equal to 1 when country i is s quarters away from the event. The lines plotted are conditional effects of being in s $\in$ [-16; 16] quarters away from the event, while the shaded area shows the confidence band (95%). A value different from zero means that the variable takes values that deviate from those in "normal times".

Figure 2. : Behaviour of financial and economic conditions around the financial crises



Notes: Figures show the results from the following fixed effect panel specification on 21 advanced economies: $y_{it} = \alpha_i + \beta_{ds}\delta_{ds} + \varepsilon_{it}$, where δ_{is} denotes dummy variable equal to 1 when country i is s quarters away from the event. The lines plotted are conditional effects of being in s $\in$ [-16; 16] quarters away from the event, while the shaded area shows the confidence band (95%). A value different from zero means that the variable takes values that deviate from those in "normal times".

B. *The effect of financial indicators on the probability of a crisis*

Based on our sample, we estimate the probability of starting to be in a financial crisis.[11] Our dependent variable takes the value of one if the financial crisis starts in country i at quarter t and zero otherwise. Using the logit specification, the probability of a financial crisis starting in country i in quarter t is given by

$$p_{i,t} = \frac{exp(\mu_i + \mu_L L_{i,t})}{exp(\beta_{j,s}\lambda_{j,i,s})} + \varepsilon_{j,i,t}, \tag{2}$$

where μ_i are the country fixed effects. μ_L are the coefficients on the set of financial imbalances, including a set of macro controls such as lag GDP growth and inflation. Table 2 shows the estimates. We also tested for different specifications if the area under the curve (AUC) exceeds 0.5 for the null to be rejected. The AUCs are all above 0.70, particularly high for the main specification in column (1).[12] The estimates suggest that the steady-state (annual) probability of a crisis is about 1.7%. Further, all the selected financial imbalances measures positively affect the probability of a crisis.

C. *The effect of financial imbalances on the severity of a financial crisis*

In our framework, we are interested in how financial imbalance accumulation affects the path of real GDP and other macro variables during busts. To this end, we use local projection methods (Jordà, 2005; Cloyne, Jordà and Taylor, 2023) to estimate how the excess credit affects the real GDP path during a normal recession and financial crisis. The local projections can accommodate the nonlinearities in our model specification estimated in a simple univariate framework, preserving valuable degrees of freedom.[13]

For any variable $k = 1, \cdots, K$, we want to characterise the change of variables from the start of the crisis to some horizon $h = 1, \cdots, H$.[14] Local projections are based on sequential regressions of the endogenous variable shifted forward:

(3)

$$\Delta_h y^k_{it+h} = \alpha^k_i + \theta^k_N S^N_{i,t} + \theta^k_F S^F_{i,t} + \beta^k_{h,F} S^F_{i,t}(x_{it} - \bar{x_i}) + \sum_{l=0}^{L} \Gamma^k_{h,l} \Upsilon_{it-l} + \varepsilon^k_{h,it} \quad \text{for all } k > 0 \text{ and } h > 0,$$

where α^k_i is country fixed effect; ε is the error term; y is a variable of interest, for example, real GDP; x_{it} denotes the accumulated change of the financial variable

[11] Similar exercises were performed by estimating the probability below the 10th percentile of the next three years' real GDP growth distribution.

[12] For robustness checks, we also run similar exercises excluding one country each time.

[13] Although the local projection method allows for more flexibility by imposing weaker assumptions on the dynamics, its nonparametric nature comes at an efficiency cost.

[14] Due to the inherent serial correlation in the local projections approach, we use Newey-West standard errors.

Table 2—: Estimated parameters in the logit model

	Start financial crisis: one-year ahead			
VARIABLES	(1)	(2)	(3)	(4)
Real credit growth (5y)	0.266***			
	(0.078)			
Return on equity (3y)	0.034***	0.037**	0.026**	0.037**
	(0.013)	(0.017)	(0.013)	(0.016)
House prices/income (5y)	0.128**	0.145**	0.108	0.143**
	(0.062)	(0.065)	(0.082)	(0.063)
Real interest rate (3y)	0.745**	0.788**	0.754*	0.789**
	(0.370)	(0.374)	(0.409)	(0.376)
Real NFC credit growth (5y)		0.233***		0.229***
		(0.050)		(0.061)
Real HH credit growth (5y)			0.087	0.006
			(0.063)	(0.067)
Constant	-5.444***	-5.197***	-4.791***	-5.203***
	(0.506)	(0.403)	(0.478)	(0.415)
Observations	2,314	2,127	2,127	2,127
Country fixed effects	YES	YES	YES	YES
Pseudo R^2	0.165	0.156	0.115	0.156
Area under the curve (AUC)	0.847	0.852	0.797	0.852

Notes: Clustered standard errors are reported in parentheses, and the asterisks denote significance levels: *** p<0.01, ** p<0.05, * p<0.1. Additional controls, such as inflation and GDP growth, are included.

at time t for country i with the long-run mean, $\bar{x}_i$. θ^k_N is the constant associated with the normal recession[15] $S^N_{i,t} = 1$ (0 otherwise). θ^k_F is the constant associated with the financial crisis recession $S^F_{i,t} = 1$ (0 otherwise) described in the previous section. $S^N_{i,t}$ and $S^F_{i,t}$ measure the average cumulated response in normal recession and financial crisis, respectively. When x_{it} is deviating from $\bar{x}_i$ before a financial crisis, the marginal effect is given by $\beta^k_{h,F}$ in addition to θ^k_F. $\Gamma^k_{h,l}$ reflects the coefficient matrices for a history of l lags for the control variables Υ_{it-l}. We employ several controls: real GDP growth rate, inflation rate, current account to GDP ratio, short-term interest rates, and real investment growth rate. We also control credit growth, real house price growth, and real return on equity, which tend to attenuate any effects we measure through x.

Figure 3 shows the local projection results from equation 3 for real GDP, real

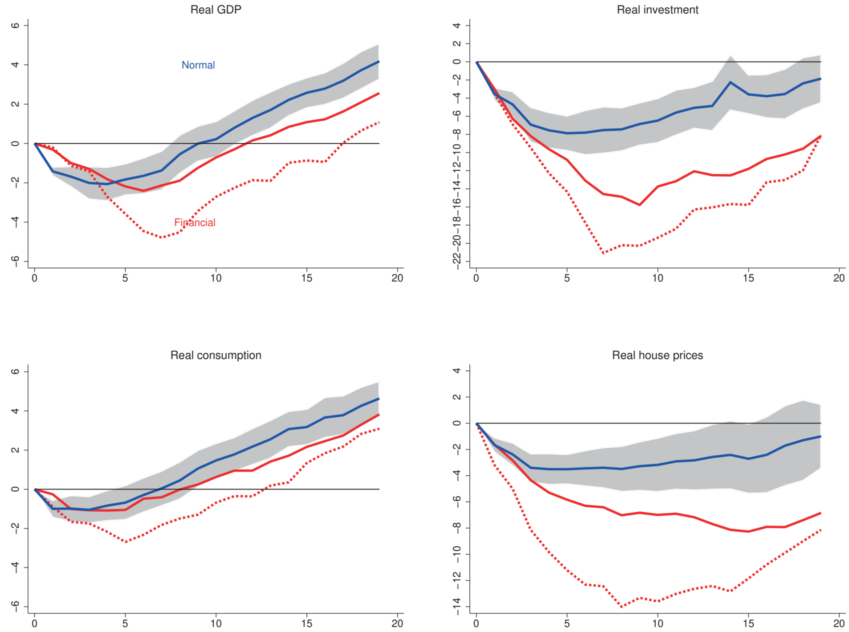
[15] We defined normal recession as two consecutive quarters of negative GDP growth.

consumption, real investment, and real house price. The paths reflect the conditional cumulative change of selected variables from the start of the recession as a function of the size of the preceding private credit boom and the type of recession. The solid blue line depicts the average effect of a "normal" recession with 95% confidence bands shown as grey areas. The solid red line reflects the average effect of a financial crisis. The dashed red line represents the combined effect of a financial crisis and one standard deviation of excess credit growth. In a normal recession, real GDP declines as much as 2% in a year, recovering the original level by around two years and then continuing to grow. However, financial crises are more pronounced and take more time to recover. If excess credit exists, the loss of output is pronounced in a financial crisis. Real investment falls substantially more than consumption. Real house prices tend to fall considerably in financial crises, particularly with pre-existing excess credit. The difference between the two paths is also significant.[16] Our results align with the results of Jordà, Schularick and Taylor (2013) and suggest that "credit bites back."[17]

[16] In the appendix, Table A.1 provides the local projection coefficient estimates together with robust standard errors and formal test of the equality of the average responses crisis.

[17] In the appendix, Figures A.2, A.3, and A.4 show the results from macro and financial variables during a financial turmoil state conditional on the pre-crisis of the other financial imbalances indicators.

Figure 3. : Conditional cumulative change from the start of the recession



Notes: The figure plots the marginal impact on real GDP following a change in financial indicators. All variables are in log terms × 100. The solid blue line depicts the average effect of a "normal" recession with 95% confidence bands shown as grey areas. The solid red line reflects the effect of a financial crisis. The dashed line represents the combined effect of a financial crisis and one standard deviation of excess credit growth. Excess credit (followed by financial crisis) refers to the marginal effect of excess credit accumulation above the historical mean on the average path in a financial crisis. Therefore, when excess credit is one standard deviation above the mean, the path of a financial crisis's macro or financial variables can be computed as the sum of the financial recession coefficient and the excess credit.

III. A Regime-Switching DSGE Model of Financial Imbalances

In this section, we rationalise the empirical findings mentioned above in a Markov regime-switching version of a canonical New Keynesian DSGE model with the banking and housing sectors that explicitly considers the nonlinearities stemming from financial imbalances and prolonged financial cycles.

The model economy closely follows Gerali et al. (2010) at its core but is extended to include endogenous financial crises based on credit imbalances via a Markov regime-switching framework and persistent financial cycles via hybrid house price expectations as in Gelain, Lansing and Mendicino (2013). We first describe the constant-parameter version of the model in detail. We then elaborate on how we incorporate regime-switching ingredients into the model.

The economy consists of two types of households: patient (P) and impatient (I), and entrepreneurs with a unit mass for each. Both types of households consume, work, and demand housing services. Patient households save via deposits, whereas impatient households borrow from banks to buy houses. Entrepreneurs use capital and labour to produce intermediate goods. They purchase capital from capital-good producers. Households and entrepreneurs differ in their degree of impatience. The discount factor of patient households is higher than that of impatient households and entrepreneurs. This ensures that the latter group borrows from the former in equilibrium.

Impatient households and entrepreneurs also face collateral constraints when they borrow from the banking sector. Impatient households can borrow against the value of their houses, while entrepreneurs can borrow against the value of their physical capital. Banks collect deposits from patient households and combine them with their equity capital (retained earnings) to extend loans to impatient households and entrepreneurs. The banking sector exhibits characteristics of monopolistic competition. They maximise their profits by setting deposit rates together with household and business lending rates.

Each household supplies a differentiated labour input via unions to the intermediate goods-producing firms. Wages are set by households under the assumption of monopolistic competition. In addition to entrepreneurs, capital goods and housing producers set the market price for capital and houses. Finally, the monopolistically competitive retail sector purchases intermediate goods from entrepreneurs differentiates them, and prices them subject to nominal rigidities.

A. Patient households

Patient households obtain utility from consumption, leisure, housing services, and deposits. Preferences are additively separable. Lifetime expected utility of a patient household j at time s is given by

$$U_s(j) = E_s \sum_{t=s}^{\infty} \beta_P^{t-s} \left[u\left(C_t^P(j)\right) + d(D_t(j)) + w(H_t^P(j)) - v(L_t^P(j)) \right], \tag{4}$$

where β_P is the discount factor of patient households, C_t^P denotes their consumption basket, D_t is deposits, H_t^P denotes their housing stock and L_t^P is their supply of labour. Their instantaneous utility function is given by

$$u\left(C_t^P(j)\right) = z_t^u (1 - b^c) \ln \left[\frac{C_t^P(j) - b^c C_{t-1}^P}{1 - b^c} \right], \tag{5}$$

$$d\left(D_t(j)\right) = z_t^d \ln \left[D_t(j)\right], \tag{6}$$

$$v\left(L_t^P(j)\right) = \frac{\nu^p}{1+\phi} \left[L_t^P(j)\right]^{1+\phi}, \tag{7}$$

$$w(H_t^P(j)) = z_t^h \ln \left[H_t^P(j)\right], \tag{8}$$

where z_t^u is a shock to consumption preferences, z_t^d is a shock to deposit supply, and z_t^h is a shock to housing demand.[18] They all follow AR(1) processes. b^c governs habit persistence in consumption. The inverse of the Frisch elasticity of labour supply is given by $\phi > 0$. The Frisch elasticity captures the elasticity of hours worked to the wage rate. Patient household j's budget constraint in period t is as follows:

$$\begin{aligned} & P_t C_t^P(j) + P_t D_t(j) + P_t^H H_t^P(j) \\ & = W_t(j) L_t^P(j) \left[1 - \gamma_t(j)\right] + R_{t-1}^d P_{t-1} D_{t-1}(j) \\ & + (1 - \delta_H) P_t^H H_{t-1}^P(j) + DIV_t^P(j) - TAX_t^P(j), \end{aligned} \tag{9}$$

where P_t is the price level of final goods, P_t^H is the price level of housing services, R_t^d is the gross interest on the household's deposits, $W_t(j)$ is the nominal wage rate in the intermediate goods sector set by household j, $\gamma_t(j)$ is the wage adjustment cost (defined below in (17)), $L_t^P(j)$ is the amount of hours worked in the intermediate goods sector, and δ_H denotes the depreciation rate of the housing stock. $DIV_t^P(j)$ and $TAX_t^P(j)$ are dividends[19] (in nominal terms) disbursed to household j and lump-sum taxes paid by household j, respectively. Hence, equation (9) states that the expenses on consumption and housing services together with savings via deposits need to be equal to the sum of labour income (net of adjustment costs), deposits from the previous period with interest income, and undepreciated housing stock plus any dividends (and other lump-sum income) less taxes.

[18] The log in-period utility functions for consumption, deposits, and housing imply an intertemporal elasticity of substitution equal to 1, which secures a balanced growth path.

[19] It includes any entrepreneurial surplus (see Section III.G).

B. Impatient households

Impatient households obtain utility from consumption, leisure, and housing services. Their preferences are also additively separable. Lifetime expected utility of an impatient household j at time s is given by

$$U_s(j) = E_s \sum_{t=s}^{\infty} \beta_I^{t-s} \left[u\left(C_t^I(j)\right) + w(H_t^I(j)) - v(L_t^I(j)) \right], \tag{10}$$

where β is the discount factor of impatient households, C_t^I denotes their consumption, H_t^I is their housing stock, and L_t^I denotes their supply of labour. Their instantaneous utility functions are defined as follows:

$$u\left(C_t^I(j)\right) = z_t^u (1 - b^c) \ln \left[\frac{C_t^I(j) - b^c C_{t-1}^I}{1 - b^c} \right], \tag{11}$$

$$v\left(L_t^I(j)\right) = \frac{\nu^p}{1+\phi} \left[L_t^I(j) \right]^{1+\phi}, \tag{12}$$

$$w(H_t^I(j)) = z_t^h \ln \left[H_t^I(j) \right], \tag{13}$$

where z_t^u is a shock to consumption preferences, and z_t^h is a shock to housing demand. These shocks also follow AR(1) processes. b^c governs habit persistence in consumption. The inverse of the Frisch elasticity of labour supply is given by $\phi > 0$.

Impatient household j's budget constraint in period t is given by

$$\begin{aligned} &P_t C_t^I(j) + P_t^H H_t^I(j) + \left(1 + r_{t-1}^F(j)\right) P_{t-1} B_{h,t-1}(j) \\ &= W_t(j) L_t^I(j) \left[1 - \gamma_t(j)\right] + P_t B_{h,t}(j) \\ &+ (1 - \delta_H) P_t^H H_{t-1}^I(j) + DIV_t^I(j) - TAX_t^I(j), \end{aligned} \tag{14}$$

where P_t reflects the price level of final goods, P_t^H is the price level of housing services, r_t^F denotes the nominal net mortgage interest rate faced by households, $B_{h,t}(j)$ indicates real household borrowing (or mortgage), $W_t(j)$ is the nominal wage rate in the intermediate goods sector set by household j, $\gamma_t(j)$ is the wage adjustment cost (defined below in (17)), $L_t^I(j)$ represents the amount of hours worked in the intermediate goods sector, and δ_H denotes the depreciation rate of the housing stock. $DIV_t^I(j)$ and $TAX_t^I(j)$ are dividends (in nominal terms) disbursed to household j and lump-sum taxes paid by household j, respectively. Hence, equation (14) states that expenses on consumption, housing services, and interest and principal payments on the mortgage need to be equal to the sum of labour income (net of adjustment costs), new mortgage, and undepreciated housing stock plus any dividends (and other lump-sum income) less taxes.

Following Iacoviello (2005) and Gerali et al. (2010), we assume that impatient households are credit constrained. In particular, the borrowing constraint postulates that the interest and principal payments on the mortgage must be less than or equal to the expected value of the housing wealth of impatient households.

$$(1 + r_t^F(j)) P_t B_{h,t}(j) \leq \phi_t^H E_t \left[\frac{P_{t+1}^H}{P_{t+1}} \frac{P_{t+1}}{P_t} H_t(j) \right], \tag{15}$$

where ϕ_t^H is the time-varying LTV ratio for mortgages, which follows an AR(1) process. A shock to ϕ_t^H represents a disturbance to loan-to-value (LTV) ratio for household borrowing. An increase in house prices raises the collateral values of houses, expanding households' capacity to borrow more and thus creating a demand for mortgages, the proceeds of which are spent on consumption goods, housing, and deposits.

C. Labour market

The labour market is characterised by monopolistic competition. Households supply labour and set wages subject to demand from the intermediate goods sector. Real wages are set as a markup over the marginal rate of substitution of consumption for leisure. Household j faces the following labour demand curve from the intermediate goods sector:

$$L_t(j) = \left(\frac{W_t(j)}{W_t} \right)^{-\psi_t} L_t, \tag{16}$$

where W_t is the wage rate and ψ_t is the elasticity of substitution between differentiated labour. It follows an AR(1) process and can be interpreted as an inverse wage markup shock. In addition, there is sluggish wage adjustment due to adjustment costs measured in terms of the total wage bill (cf. Kim (2000)). Wage adjustment costs are specified as:

$$\gamma_t(j) = \frac{\phi^W}{2} \left[\frac{W_t(j)/W_{t-1}(j)}{W_{t-1}/W_{t-2}} - 1 \right]^2. \tag{17}$$

As seen from equation (17), costs are related to changes in individual wage inflation relative to the past observed rate for the whole economy. The parameter $\phi^W > 0$ determines how costly it is to change the wage inflation rate.

D. Equilibrium conditions of patient households

Maximising utility, equation(4), subject to the budget constraint, equation (9), gives the first-order conditions with respect to deposits, D_t, the wage rate, W_t, and housing, H_t^P below:

$$E_t\left[\Delta_{t+1}^P\right]R_t^d - 1 = -\frac{d'(D_t)}{u'\left(C_t^P\right)}, \tag{18}$$

$$\begin{aligned}\frac{v'\left(L_t\right)}{u'\left(C_t^P\right)}\psi_t\frac{P_t}{W_t} = &\left[\left(\psi_t-1\right)\left(1-\gamma_t\right)+\phi^W\left(\frac{W_t/W_{t-1}}{W_{t-1}/W_{t-2}}-1\right)\frac{W_t/W_{t-1}}{W_{t-1}/W_{t-2}}\right]\\ &-E_t\left[\Delta_{t+1}^P\frac{L_{t+1}}{L_t}\phi^W\left(\frac{W_{t+1}/W_t}{W_t/W_{t-1}}-1\right)\frac{\left(W_{t+1}/W_t\right)^2}{W_t/W_{t-1}}\right],\end{aligned} \tag{19}$$

$$\frac{w'(H_t^P)}{u'\left(C_t^P\right)} = \frac{P_t^H}{P_t} - \left(1-\delta_H\right)E_t\left[\Delta_{t+1}^P\frac{P_{t+1}^H}{P_t}\right], \tag{20}$$

where we define the stochastic discount factor as $\Delta_{t+1}^P \equiv \beta\frac{u'\left(C_{t+1}^P\right)}{u'\left(C_t^P\right)}\frac{P_t}{P_{t+1}}$ and suppress household indicator j.

Equation (18) states that the marginal rate of substitution between deposits and consumption must be equal to the marginal benefit of holding deposits, which is the deposit rate. Compared with a canonical dynamic stochastic general equilibrium (DSGE) model, the household faces an additional opportunity cost of consuming in the current period in the form of lost utility from deposits. Equation (19) is the first-order equation with respect to the wage rate, which is set by households subject to the demand function in (16). In the special case without any wage adjustment costs, $\phi^W = \gamma_t = 0$ (see equation (17)), (19) will simply be reduced to $\frac{W_t}{P_t} = \frac{\psi_t}{\psi_t - 1}\frac{v'(L_t)}{u'\left(C_t^P\right)}$. The real wage rate is set as a markup over the marginal rate of substitution between leisure and consumption. The second term on the right-hand side of (19) captures the adjustment costs of a change in wages, whereas the last term reflects that increasing wages today reduces the need to increase wages in the future. Therefore, households consider the full path of future labour demand when setting the current wage level. Equation (20) sets the marginal rate of substitution between housing and consumption to the effective price of housing. The first term on the right-hand side is the real house price, and the second part is the net-of-depreciation continuation value.

E. Equilibrium conditions of impatient households

Maximising utility, (10), subject to the budget constraint, (14), and the borrowing constraint, (15) gives the first-order conditions with respect to mortgage borrowing, $B_{h,t}$, the wage rate, W_t, and housing, H_t^I below:

$$1 - \frac{\omega_t}{u'\left(C_t^I\right)}R_t^F = E_t[\Delta_{t+1}]R_t^F \tag{21}$$

$$\frac{v'(L_t)}{u'\left(C_t^I\right)}\psi_t\frac{P_t}{W_t} = \left[(\psi_t - 1)(1-\gamma_t) + \phi^W\left(\frac{W_t/W_{t-1}}{W_{t-1}/W_{t-2}} - 1\right)\frac{W_t/W_{t-1}}{W_{t-1}/W_{t-2}}\right] \tag{22}$$
$$-E_t\left[\Delta_{t+1}^I\frac{L_{t+1}}{L_t}\phi^W\left(\frac{W_{t+1}/W_t}{W_t/W_{t-1}} - 1\right)\frac{(W_{t+1}/W_t)^2}{W_t/W_{t-1}}\right],$$

(23)
$$\frac{w'(H_t)}{u'\left(C_t^I\right)} = \frac{P_t^H}{P_t} - (1-\delta_H)E_t\left[\Delta_{t+1}^I\frac{P_{t+1}^H}{P_t}\right] - \frac{\omega_t}{u'(C_t)}\frac{\phi_t^H}{1+\phi_t^H}E_t\left[\frac{P_{t+1}^H}{P_{t+1}}\frac{P_{t+1}}{P_t}\right],$$

where we define the stochastic discount factor as $\Delta_{t+1}^I \equiv \beta\frac{u'\left(C_{t+1}^I\right)}{u'\left(C_t^I\right)}\frac{P_t}{P_{t+1}}$, suppress household indicator j, and denote ω_t as the Lagrangian multiplier associated with (15).

Equation (21) states that households would take up mortgages up to a point where the effective cost of borrowing is equal to the shadow marginal benefit of a mortgage. Equation (23) sets the marginal rate of substitution between housing and consumption to the effective price of housing. The first term on the right-hand side is the real house price, the second part is the net-of-depreciation continuation value, and the last term captures that the increase in the household's collateral from more housing induces the household to take up more mortgage debt. The increase in collateral is valued at the shadow value of additional mortgage debt.

F. House price expectations

Agents in the model are forward-looking and have model-consistent expectations. A noteworthy exception is house price expectations, where we introduce so-called hybrid expectations as in Gelain, Lansing and Mendicino (2013). We assume that a share b^{sa} of households expects house prices to follow a moving average process (i.e., partly backward-looking expectations), whereas a share $(1-b^{sa})$ has rational expectations (in log-gap form). This generates prolonged financial cycles more in line with empirical evidence:

$$E_t\left[\widehat{P_{t+1}^H}\right] = b^{sa}\widehat{X_t^H} + (1-b^{sa})\widehat{P_{t+1}^H}, \tag{24}$$

where $\widehat{}$ denotes gap-form and the moving average process is defined as

$$\widehat{X_t^H} = \lambda^{sa}\widehat{P_{t-1}^H} + (1-\lambda^{sa})\widehat{X_{t-1}^H}. \tag{25}$$

G. Entrepreneurs

Each entrepreneur i maximises the utility function below

$$U_s^E(i) = E_s \sum_{t=s}^{\infty} \beta_E^{t-s} log(C_t^E(i) - b^E C_{t-1}^E(i)) \tag{26}$$

by choosing consumption C_t^E, physical capital K_t^E, loans from banks B_t^E, the degree of capacity utilisation u_t, and the labour inputs $L_t^{E,P}$ and $L_t^{E,I}$, for patient and impatient households, respectively, subject to the following budget constraint:

(27)

$$\begin{aligned} P_t C_t^E(i) + W_t^P L_t^{E,P}(i) + W_t^I L_t^{E,I}(i) + (1 + r_{t-1}^E) P_{t-1} B_{t-1}^E(i) \\ + Q_t^K K_t^E + P_t \psi(u_t(i))) K_{t-1}^E = P_t^W Y_t^E(i) + P_t B_t^E(i) + Q_{t-1}^K (1 - \delta^K) K_{t-1}^E(i) \end{aligned}$$

where δ^K is the depreciation rate of capital, Q_t^K is the price of capital, $\psi(u_t(i)))K_{t-1}^E$ is the real costs of changing capacity utilisation, and P_t^W is the price of the wholesale good Y_t^E produced according the production function

$$Y_t(i) = z_t^L \left[u_t(n) K_t^E(n)^{\alpha} \right] L_t^E(n)^{(1-\alpha)}, \tag{28}$$

where z_t^L is total factor productivity. Aggregate labour L_t^E combines inputs from patient and impatient households according to $L_t^E = (L_t^{E,P})^{\mu}(L_t^{E,I})^{1-\mu}$ where μ is the share of labour income of patient households.

The first term of the left-hand side of (27) is the consumption of entrepreneurs, followed by wage payments to patient and impatient households. The fourth term represents the interest and principal payments to banks on outstanding debt, while the fifth term is capital bought back from the capital producers. The last term of the left-hand side of (27) is the costs associated with a given level of the utilisation rate of capital given by

$$\gamma(u_t) = \frac{R_{K,ss}}{P_{ss}\phi_u} \left[e^{\phi_u(u_t - 1)} - 1 \right], \tag{29}$$

where ϕ_u governs the cost of adjusting the utilisation rate, and the subscript ss denotes steady-state values.

The first term on the right-hand side of (27) is the value of output followed by the business loans obtained from banks. The final term is the income generated from the sale of non-depreciated capital to the capital producers (see Section III.J). At the beginning of period t, they sell the non-depreciated capital $(1-\delta) K_{t-1}$ at price P_t^K to the capital producers. The latter combines it with investment goods to produce K_t to be sold back to entrepreneurs at the same price. To finance their activity, entrepreneurs borrow $B_{e,t}$ (referred to as corporate credit) from banks at a gross rate $R_t^E = 1 + r_t^E$, providing capital goods as collateral. They enter into a multi-period loan contract. Finally, entrepreneurs also decide the capital utilization rate u_t.

Similar to impatient households, entrepreneurs can borrow against their real capital $(1-\delta) K_t$. Their borrowing constraint is given by

$$\left(1 + r_t^E(i)\right) P_t B_{e,t}(i) \leq \phi_t^E E_t \left[\frac{Q_{t+1}^K}{P_{t+1}} \frac{P_{t+1}}{P_t} (1-\delta^K) K_t^E(i) \right] \tag{30}$$

where ϕ_t^E is the time-varying LTV ratio for business loans, which follows an AR(1) process. A shock to ϕ_t^E represents a disturbance to LTV ratio for corporate borrowing. An increase in capital prices raises the collateral values of firms, expanding their capacity to borrow more, the proceeds of which are spent on consumption goods, new capital investment, and wage payments.

Maximising utility, (26), subject to the budget constraint, (27), and the borrowing constraint, (30) gives the first-order conditions with respect to corporate borrowing, $B_{e,t}$, utilisation rate, u_t, and capital, K_t^E, below:

$$1 - \frac{\omega_t}{u'\left(C_t^E\right)} R_t^E = E_t[\Delta_{t+1}^E] R_t^E \tag{31}$$

$$\frac{R_{K,t}}{P_t} = \frac{R_{K,ss}}{P_{ss}} e^{\phi_u (u_t - 1)}, \tag{32}$$

$$\begin{aligned} \frac{Q_t^K}{P_t} &= E_t \left[\frac{\omega_t^E}{u'\left(C_t^E\right)} \frac{\phi_t^E}{1+\phi_t^E} \frac{Q_{t+1}^K}{P_{t+1}} \frac{P_{t+1}}{P_t} (1-\delta) \right] \\ &+ E_t \left[\Delta_{t+1} \frac{P_{t+1}}{P_t} \left(\frac{Q_{t+1}^K}{P_{t+1}} (1-\delta) + \frac{R_{K,t+1}}{P_{t+1}} u_{t+1} - \psi(u_{t+1}) \right) \right], \end{aligned} \tag{33}$$

Equation (31) states that entrepreneurs would receive business loans from banks up to a point where the effective cost of borrowing from them is equal to the shadow marginal benefit of these loans. Equation (32) shows that the marginal benefit of utilising an additional unit of capital is equal to the cost of using it. Finally, equation (33) states that entrepreneurs choose capital so that the marginal utility of capital on the right-hand side of (33) equals the marginal cost on the left-hand side. The first term on the right side represents the benefit of increased collateral, whereas the second term is the income from selling and renting out capital net of utilisation costs.

The structure of the banking sector builds on Gerali et al. (2010). There is an infinite number of banks in the economy, indexed by $i \in [0,1]$. Each bank consists of two retail branches and a wholesale branch. One retail branch is responsible for providing differentiated loans to households and entrepreneurs, while the other specialises in deposits. Both branches set interest rates in a monopolistically competitive manner (Hafstead and Smith, 2012), subject to adjustment costs, which leads to imperfect and sluggish interest rate pass-through from the policy rate to loan and deposit rates. The wholesale branch manages the capital position of the bank. It chooses the overall level of operations regarding deposits and lending, adhering to Gerali et al. (2010) -type capital requirements adjusted with asset-specific risk weights. Banks incur a cost if they fail to meet their capital-to-asset ratio target. Bank capital plays an important role in the model by affecting the credit supply through a feedback loop between the real and the financial sides of the economy.

The balance sheet of bank i (in real terms) is:

$$B_t(i) = D_t(i) + K_t^B(i), \tag{34}$$

where $B_t(i)$ is total assets (total lending). On the liability side, $D_t(i)$ is household deposits and $K_t^B(i)$ is bank capital (equity). Total lending is the sum of lending to entrepreneurs and households:

$$B_t(i) = B_{e,t}(i) + B_{h,t}(i). \tag{35}$$

If banks fail to meet their target level of risk-weighted capital requirements, ϖ_t, they incur a penalty cost. The target level of risk-weighted capital requirements consists of two elements: "hard" capital requirements, γ_t^b and a countercyclical capital buffer, $CCyB_t^b$, hence $\varpi_t = \gamma_t^b + CCyB_t^b$.[20] In addition, they face linear operational costs. Profits in period t for bank i as a whole are then given by:

$$J_t(i) = r_t^F(i) B_{h,t}(i) + r_t^e(i) B_{e,t}(i) - r_t^d(i) D_t(i) - \frac{\kappa_{kb}}{2}\left[\frac{K_t^B(i)}{B_t^{RW}(i)} - \varpi_t\right]^2 K_t^B(i), \tag{36}$$

where $r_t^F(i)$ is the net interest rate on loans to households, $r_t^e(i)$ is the net interest rate on loans to entrepreneurs and $r_t^d(i)$ is the net deposit interest rate. κ_{kb} denotes adjustment costs if a bank deviates from its capital target, ϖ_t. $B_t^{RW}(i)$

[20]The risk-weighted capital requirements, γ_t^b and CCB_t^b, are either shocks that follow AR(1) processes or policy rules that respond to financial variables such as credit or spreads, depending on the policy experiment. They are normally only active when the model is used for financial stability analysis. Otherwise, they are set to their steady-state values.

denotes risk-weighted assets:

$$B_t^{RW}(i) = \varsigma^e B_{e,t} + \varsigma^h B_{h,t}, \tag{37}$$

where ς^e and ς^h are the risk weights associated with credit to entrepreneurs and households, respectively. Bank capital accumulates according to:

$$K_t^B(i) = (1-\delta^b)\frac{P_{t-1}}{P_t}K_{t-1}^B(i) + \frac{P_{t-1}}{P_t}J_{t-1}(i), \tag{38}$$

where δ^b is the dividend share of the bank capital paid out to shareholders (households).

The wholesale branch

The wholesale branch lends to the loan branch at the interest rate $R_t^{b,e}(i) = 1 + r_t^{b,e}(i)$ for business credit (entrepreneurial loans) and $R_t^{b,h}(i) = 1 + r_t^{b,h}(i)$ for household loans. It is funded through borrowing from the deposit branch. The "wholesale deposit rate" is assumed to be equal to the money market rate $R_t = 1 + r_t$, which follows from a no-arbitrage condition since we assume that banks have access to unlimited financing at the money market rate.

The wholesale branch takes these funding costs as given and solves the following profit maximisation problem:

$$\begin{aligned} \max_{\{B_{h,t}(i),B_{e,t}(i),D_t(i)\}} \; & E_t\Big[R_t^{b,e}(i)B_{e,t}(i) + R_t^{b,h}(i)B_{h,t}(i) \\ & -R_t^d D_t(i)\frac{\kappa_{kb}}{2}\left[\frac{K_t^B(i)}{B_t^{RW}(i)} - \varpi_t\right]^2 K_t^B(i)\Big], \end{aligned} \tag{39}$$

subject to (34) - (35) and (37).

The first-order conditions for the wholesale bank become:[21]

$$R_t^{b,e} = R_t^d - \kappa_{kb}\varsigma^e\left[\frac{K_t^B}{B_t^{RW}} - \varpi_t\right]\left(\frac{K_t^B}{B_t^{RW}}\right)^2, \tag{40}$$

$$R_t^{b,h} = R_t^d - \kappa_{kb}\varsigma^h\left[\frac{K_t^B}{B_t^{RW}} - \varpi_t\right]\left(\frac{K_t^B}{B_t^{RW}}\right)^2. \tag{41}$$

Hence, wholesale loan rates, $R_t^{b,e}$ and $R_t^{b,h}$ are set as markups over the deposit rate, where the markups are increasing in the cost of deviating from the capital target.

We also assume that banks have unlimited access to funding from the central

[21]Since all banks behave in the same way, we have removed the index i from the first-order conditions in the banking sector section.

bank at the policy rate of R_t to close the model. By arbitrage, the household deposit rate, R_t^d, will equal the policy rate, R_t.

The loan branch

The loan branch lends to households and entrepreneurs (at net rates $r_t^F(i)$ and $r_t^e(i)$, respectively) and borrows from the wholesale branch at the net interest rates $r_t^{b,h}(i)$ and $r_t^{b,e}(i)$. When changing the loan rates, it faces costs governed by the parameters κ^{bh} and κ^{be}.

The maximisation problem for the loan branch becomes:

$$\max_{\{r_t^F(i), r_t^E(i)\}} E_s \sum_{t=s}^{\infty} \Delta_{s,t} \left[\begin{array}{c} r_t^F(i) B_{h,t}(i) + r_t^e(i) B_{e,t}(i) - r_t^{b,h}(i) B_{h,t}(i) - r_t^{b,e}(i) B_{e,t}(i) \\ -\frac{\kappa^{bh}}{2}\left(\frac{r_t^F(i)}{r_{t-1}^F(i)} - 1\right)^2 r_t^F B_{h,t} - \frac{\kappa^{be}}{2}\left(\frac{r_t^E(i)}{r_{t-1}^E(i)} - 1\right)^2 r_t^E B_{e,t} \end{array} \right],$$

subject to

$$B_t(i) = B_{e,t}(i) + B_{h,t}(i), \tag{42}$$

$$B_{h,t}(i) = \left(\frac{r_t^F(i)}{r_t^F}\right)^{-\epsilon_t^{bh}} B_{h,t}, \tag{43}$$

$$B_{e,t}(i) = \left(\frac{r_t^E(i)}{r_t^E}\right)^{-\epsilon_t^{be}} B_{e,t}. \tag{44}$$

Equations (43) and (44) are the demand functions from households and entrepreneurs, respectively, and $\epsilon_t^{bh} > 0$ and $\epsilon_t^{be} > 0$ are the elasticities of substitution between household loans and business credit from all loan branches. They follow AR(1) processes and can be interpreted as markup shocks to the lending rates for household and business loans, respectively.

The first-order condition for the loan rate to households reads as (suppressing i):

$$1-\epsilon_t^{bh}+\epsilon_t^{bh}\frac{r_t^{b,h}}{r_t^F}-\kappa^{bh}\left(\frac{r_t^F}{r_{t-1}^F}-1\right)\frac{r_t^F}{r_{t-1}^F}+E_t\left[\Delta_{t+1}\kappa^{bh}\left(\frac{r_{t+1}^F}{r_t^F}-1\right)\left(\frac{r_{t+1}^F}{r_t^F}\right)^2\frac{P_{t+1}}{P_t}\frac{B_{h,t+1}}{B_{h,t}}\right]=0. \tag{45}$$

In the absence of adjustment costs, $\kappa^{bh} = 0$, the mortgage loan rate collapses to a markup over the wholesale lending rate (which is again a markup over the policy rate (see (40)), $r_t^F = \frac{\epsilon_t^{bh}}{\epsilon_t^{bh}-1} r_t^{b,h}$. The third term in (45) ensures that the loan branch also considers future prices when setting today's price.

In a similar fashion, the first-order condition for the loan rate to entrepreneurs,

$r_t^e(i)$, becomes:
(46)

$$1-\epsilon_t^{be}+\epsilon_t^{be}\frac{r_t^{b,e}}{r_t^E}-\kappa^{be}\left(\frac{r_t^E}{r_{t-1}^E}-1\right)\frac{r_t^E}{r_{t-1}^E}+E_t\left[\Delta_{t+1}\kappa^e\left(\frac{r_{t+1}^E}{r_t^E}-1\right)\left(\frac{r_{t+1}^E}{r_t^E}\right)^2\frac{P_{t+1}}{P_t}\frac{B_{e,t+1}}{B_{e,t}}\right]=0.$$

The deposit branch

The deposit branch lends to the wholesale branch at net policy rate r_t and pays out interest on household deposits at rate $r_t^d(i)$. When changing the deposit rate, it faces costs governed by parameter κ^D. The maximisation problem becomes

$$\max_{\{r_t^d(i)\}} E_s\sum_{t=s}^{\infty}\Delta_{s,t}\left[r_tD_t(i)-r_t^d(i)D_t(i)-\frac{\kappa^d}{2}\left(\frac{r_t^d(i)}{r_{t-1}^d(i)}-1\right)^2 r_t^dD_t\right],$$

subject to deposit demand from households:

$$D_t(i)=\left(\frac{r_t^d(i)}{r_t^d}\right)^{\epsilon_t^d}D_t, \tag{47}$$

where $\epsilon^d>0$ is the elasticity of substitution between deposit services.

The first-order condition with respect to $r_t^d(i)$ becomes:
(48)

$$-(1+\epsilon^d)+\epsilon^d\frac{r_t}{r_t^d}-\kappa^d\left(\frac{r_t^d}{r_{t-1}^d}-1\right)\frac{r_t^d}{r_{t-1}^d}+E_t\left[\Delta_{t+1}\kappa^d\left(\frac{r_{t+1}^d}{r_t^d}-1\right)\left(\frac{r_{t+1}^d}{r_t^d}\right)^2\frac{P_{t+1}}{P_t}\frac{D_{t+1}}{D_t}\right]=0.$$

In the absence of adjustment costs, the deposit rate collapses to a mark-down on the policy rate ($r_t^d=\frac{\epsilon^d}{1+\epsilon^D}r_t$).

Bank profits

Bank profits are the sum of net earnings of the wholesale branch, the loan and deposit branches. After eliminating intrabank transactions, we obtain
(49)

$$j_t^b=r_t^Fb_{h,t}+r_t^eb_{e,t}-r_t^dD_t-\frac{\kappa^{bh}}{2}\left(\frac{r_t^F}{r_{t-1}^F}-1\right)^2r_t^FB_{h,t}-\frac{\kappa^{be}}{2}\left(\frac{r_t^E}{r_{t-1}^E}-1\right)^2r_t^EB_{e,t}$$
$$-\frac{\kappa^d}{2}\left(\frac{r_t^d}{r_{t-1}^d}-1\right)^2r_t^dD_t-\frac{\kappa_{kb}}{2}\left[\frac{K_t^B}{B_t^{RW}}-\varpi_t\right]^2K_t^B$$

Equation (49) net of adjustment costs includes the earnings from interest rate margins and abstracts from other items, such as other operating expenses in the income statement.

I. *Retail sector*

The retail sector is assumed to be monopolistically competitive, as in Gerali et al. (2010). Their prices are sticky and are indexed to a combination of past and steady-state inflation with relative weights denoted by ι_p. They face adjustment costs when changing nominal prices as in Rotemberg (1982).

The maximisation problem

Retail firms face the following price adjustments costs per value unit:

$$\gamma_{P,t}(n) \equiv \frac{\kappa^P}{2}\left[\frac{P_t}{P_{t-1}} - \pi_{t-1}^{\iota_p}\pi^{1-\iota_p}\right]^2, \tag{50}$$

where P_t is the price of the final good. The costs of changing prices are governed by the parameter ϕ^P.[22] One can show that the firms face the following demand functions from the final goods sector:

$$y_t(n) = \left(\frac{P_t\,(n)}{P_t}\right)^{-\epsilon_t^y} y_t, \tag{51}$$

where ϵ_t^y is the elasticity of substitution between goods produced by different firms in the retail sector and follows an AR(1) process, which can be interpreted as a price (inverse) markup shock.

Profit maximisation gives rise to the following first-order condition for price-setting, P_t:

$$\begin{aligned} &y_t - \epsilon_t^y y_t + P_t^W \epsilon_t^y \frac{y_t}{P_t} - \kappa^P\left[\frac{P_t}{P_{t-1}} - \pi_{t-1}^{\iota_p}\pi^{1-\iota_p}\right]\frac{P_t}{P_{t-1}} y_t \\ &+E_t\left\{\Delta_{t+1}\kappa^P\left[\frac{P_{t+1}}{P_t} - \pi_t^{\iota_p}\pi^{1-\iota_p}\right]\frac{P_{t+1}}{P_t} y_{t+1}\right\} = 0, \end{aligned} \tag{52}$$

Equation (52) is the New Keynesian Philips curve for prices. In the absence of adjustment costs, $\kappa^P = 0$, prices would be set as a markup over marginal costs in every period $P_t = \frac{\epsilon_t^y}{\epsilon_t^y - 1} P_t^W$ (where $\epsilon_t^y > 1$). The fourth term captures the adjustment costs of the price change, whereas the last term reflects that increasing the price in the current period reduces the need to increase prices further in the future. Hence, the latter term implies that firms consider the full path of future demand when setting prices.

[22] Similar to wage adjustment costs, price adjustment costs are related to changes in inflation for firm n relative to the past observed rate for the whole economy.

J. Capital producers

Capital goods, K_t, are produced by separate producers. At the beginning of period t capital goods producers buy undepreciated capital $(1-\delta)\,K_{t-1}$ at a price Q_t^K from entrepreneurs and combine it with (gross) investment goods $I_{C,t}$ to produce K_t to be sold back to entrepreneurs at the same price. The capital producers operate in a perfectly competitive market and, therefore, earn no profit. $I_{C,t}$ is bought from the final goods sector at a price P_t.

The representative capital producer h maximises the following function

$$\max_{\{I_{C,t}(h)\}} \left[Q_t^K K_t(h) - Q_t^K\,(1-\delta)\,K_{t-1}(h) - P_t I_{C,t}(h)\right],$$

subject to the capital accumulation equation:

$$K_t(h) = (1-\delta)K_{t-1}(h) + \kappa_t(h) I_{C,t}(h). \tag{53}$$

The last term, $\kappa_{C,t}(h)I_{C,t}(h)$, can be thought of as "net investment", i.e. investment net of adjustment costs:

$$\kappa_{C,t}(h) = \left[1 - \frac{\kappa_i}{2}\left(\frac{I_{C,t}(h)\epsilon_t^{qk}}{I_{C,t-1}(h)} - 1\right)^2\right] \tag{54}$$

The parameter κ_i governs the degree of adjustment costs, and ϵ_t^{qk} is a shock to the efficiency of business investment that follows an AR(1) process.

Maximisation with respect to $I_{C,t}$ gives the following first-order condition, suppressing indicator h:

$$\begin{aligned}\frac{Q_t^K}{P_t} = \Bigg[\Bigg\{ 1 - \frac{\kappa_i}{2}\left(\frac{I_{C,t}\epsilon_t^{qk}}{I_{C,t-1}} - 1\right)^2 - \kappa_i\left(\frac{I_{C,t}\epsilon_t^{qk}}{I_{C,t-1}} - 1\right)\left(\frac{I_{C,t}\epsilon_t^{qk}}{I_{C,t-1}}\right)\Bigg\} \\ + E_t\left\{\Delta_{t+1}^E \frac{Q_{t+1}^K}{Q_t^K}\frac{P_t}{P_{t+1}}\kappa_i\left(\frac{I_{C,t+1}\epsilon_{t+1}^{qk}}{I_{C,t}} - 1\right)\epsilon_{t+1}^{qk}\left(\frac{I_{C,t+1}}{I_{C,t}}\right)^2\right\}\Bigg]^{-1}.\end{aligned} \tag{55}$$

Based on the movements in the adjustment costs in the two bracketed terms in (55), the real price of capital fluctuates around its steady-state level of 1.

K. Housing producers

The housing producers' production function and housing capital accumulation constraint are similar to those of the capital producers. At the beginning of period t, the housing producers buy the undepreciated housing stock $(1-\delta_H)\,H_{t-1}$ at a price P_t^H from households and combine it with housing investment goods $I_{H,t}$ to produce H_t to be sold back to households at the same price. The housing producers also operate in a perfectly competitive market and earn no profit. $I_{H,t}$ is bought from the final goods sector at a price P_t. The representative housing producer f maximizes

$$\max_{\{I_{H,t}(f)\}} \left[P_t^H H_t(f) - P_t^H (1-\delta_H) H_{t-1}(f) - P_t I_{H,t}(f)\right],$$

subject to the housing accumulation equation:

$$H_t(f) = (1-\delta_H)H_{t-1}(f) + \gamma_{H,t}(f) I_{H,t}(f), \tag{56}$$

where $\gamma_{H,t}(f)I_{H,t}(f)$ is "net housing investment" and $\kappa_{H,t}(f)$ is defined as

$$\kappa_{H,t}(f) = \left[1 - \frac{\kappa_h}{2}\left(\frac{I_{H,t}(f)\epsilon_t^{qh}}{I_{H,t-1}(f)} - 1\right)^2\right] \tag{57}$$

The parameter κ_h governs the degree of adjustment costs, and ϵ_t^{qh} is a shock to the efficiency of residential investment that follows an AR(1) process. The first-order condition with respect to $I_{H,t}$ becomes, analogously to (55) (suppressing index f):

$$\begin{aligned} \frac{Q_t^H}{P_t} = & \left[\left\{1 - \frac{\kappa_h}{2}\left(\frac{I_{H,t}\epsilon_t^{qh}}{I_{H,t-1}} - 1\right)^2 - \kappa_h\left(\frac{I_{H,t}\epsilon_t^{qh}}{I_{H,t-1}} - 1\right)\left(\frac{I_{H,t}\epsilon_t^{qh}}{I_{H,t-1}}\right)\right\}\right. \\ & \left. + E_t\left\{\Delta_{t+1}^H \frac{Q_{t+1}^H}{Q_t^H}\frac{P_t}{P_{t+1}}\kappa_h\left(\frac{I_{H,t+1}\epsilon_{t+1}^{qh}}{I_{H,t}} - 1\right)\epsilon_{t+1}^{qh}\left(\frac{I_{H,t+1}}{I_{H,t}}\right)^2\right\}\right]^{-1}. \end{aligned} \tag{58}$$

L. Monetary policy and market clearing

The central bank follows the Taylor rule while setting the policy rate:

$$(1+r_t) = (1+r)^{1-\phi_R}(1+r_{t-1})^{\phi_R}\left(\frac{\pi_t}{\pi}\right)^{\phi_\pi(1-\phi_R)}\left(\frac{Y_t}{Y_{t-1}}\right)^{\phi_y(1-\phi_R)}\epsilon_t^r \tag{59}$$

where ϕ_π is the weight assigned to inflation stabilisation, ϕ_y is the weight assigned to output growth, r is the steady-state policy rate, and ϵ_t^r is the i.i.d. shock to monetary policy rate with a standard deviation of σ_r.

The goods' market clearing condition is given by

$$y_t = c_t + i_{c,t} + i_{h,t} + g_t \tag{60}$$

M. Regime-switching features of the model

In this section, we present the regime-switching features of the model described above. In particular, normal and crisis times are governed by a Markov process in the model. The probability of a crisis starting increases with pre-existing imbalances in real private credit, real house and equity prices, and real interest rates. In addition, the severity of such turmoil, if materialised, can be amplified by the degree of imbalances in real private credit. The crisis path is driven by a combination of shocks scaled by the size of financial imbalances and structural changes in the housing and financial sectors. In addition, ELB on interest rates is governed by a separate Markov process. Whenever the nominal policy rate implied by the monetary policy rule falls below the ELB rate, it is endogenously set to the ELB rate. The probability of hitting the ELB is given by another logistical function that depends on the distance between the monetary policy rule-implied rate and the ELB rate.

The severity of a crisis

The crisis regime is calibrated to obtain a financial crisis similar to those observed in the actual data. We replicate the dynamic behaviour of several macroeconomic and financial aggregates in a typical domestic financial recession.

We achieve this by translating the narrative to shocks hitting the economy in a crisis. Shocks to household and business credit spreads are used to motivate the sharply tightening financial conditions during financial crises. In addition, shocks to household and business LTV ratios proxying additional credit supply shocks in terms of quantity restrictions reflect tighter lending standards by banks during these episodes. Credit demand shocks, modeled using shocks to housing preferences, are motivated by the decline in household credit demand due to the fall in house prices and, hence, the collateral values of houses. Shocks to household savings via deposits at banks are used to reflect the fact that households draw down their accumulated savings to smooth their consumption during these episodes. Therefore, the fall in consumption is less severe than the decline in output. Last but not least, we use government spending shocks to match fiscal stimulus measures implemented during financial turmoil periods. We also incorporate two behavioural changes in households and businesses in these times by using regime-specific dynamic parameters of housing and business investment adjustment costs. Both non-financial businesses and housing construction firms reduce their investment substantially more during crisis episodes compared to normal times.

In our model, we want to capture the stylised fact that a buildup in financial imbalances precedes crisis episodes and the size of the imbalances correlate with the severity of the following crisis (see e.g. Borio and Lowe (2004). Therefore, the shock innovations for the structural shock processes outlined above consist of typical business cycle innovations and a crisis innovation:[23]

$$log(Z_t^i) = (1 - \rho^{Z^i})log(Z_{ss}^i) + \rho^{Z^i} log(Z_{t-1}^i) + \epsilon_{Z,t}^i - \beta^{Z^i} log(crisis_t) \tag{61}$$

where Z_t^i is a generic business cycle shock, Z_{ss}^i is the steady state (SS) level of the shock process, ρ^{Z^i} is the persistence parameter, $\epsilon_{Z,t}^i$ is the shock innovation, β^{Z^i} is a scale factor for each crisis shock innovation, and $crisis_t$ is a shock, which is only active once the economy enters a crisis, and follows

$$log(crisis_t) = \rho_{crisis} log(crisis_{t-1}) + \Omega\kappa_t \tag{62}$$

where ρ_{crisis} is the persistence of the crisis shock. Ω is a crisis indicator variable. In normal times we have $\Omega = 0$, and in crisis times $\Omega = 1$. κ_t is a variable that captures the severity of crises. The severity, κ_t, is a function of credit imbalances, $B_{h,t}^{5y}$:

$$\kappa_t = (1 - \Omega)(\gamma + \gamma_B B_t^{5y}) + \rho_\kappa \Omega \kappa_{t-1} \tag{63}$$

where B_t^{5y} is the five-year average real private credit growth, γ governs a constant effect of credit imbalances on the respective crisis shock and γ_B governs the effect of the initial level of credit imbalances on crisis severity. β^{Z^i}, ρ_{crisis}, γ, and γ_{B_h} are calibrated to match the asymmetric effect of a crisis on each crisis shock, the persistence of crisis shocks, the baseline severity and the additional severity of crises due to higher pre-crisis credit growth, respectively.

We calibrate the parameters for crisis severity, γ and γ_B, such that the model-based effect of pre-crisis credit growth on output during crises virtually matches, on average, the severity of financial crises observed in advanced economies. This is also in the range of the severity of different types of financial crises that occurred in the European Union, described in Duca et al. (2017) in more detail and in Claessens, Kose and Terrones (2014) for the OECD countries. Figure 4 shows the dynamics of the output gap during financial crises in the model when pre-crisis five-year cumulative real household credit growth is at its average (solid line) and when it is one standard-deviation higher than its average (dashed line).

The figure indicates that output falls by 2.5% on average at its lowest point during a financial crisis when pre-crisis real private credit growth is at its average. However, when pre-crisis credit growth is one standard-deviation higher than its average, output declines by about 5% at its lowest point. Considering that the standard-deviation of five-year average growth in real household credit is 2.43%, output declines by 2.5/2.43 = 1.02 percentage point more on average during financial crises if five-year average real credit growth is 1 percentage point higher before the crisis. Moreover, the impact of a financial crisis on output is very persistent, with output still below its pre-crisis level two years after the end

[23] A similar setup is used in Gerdrup et al. (2017); Kravik, Kockerols and Mimir (2023).

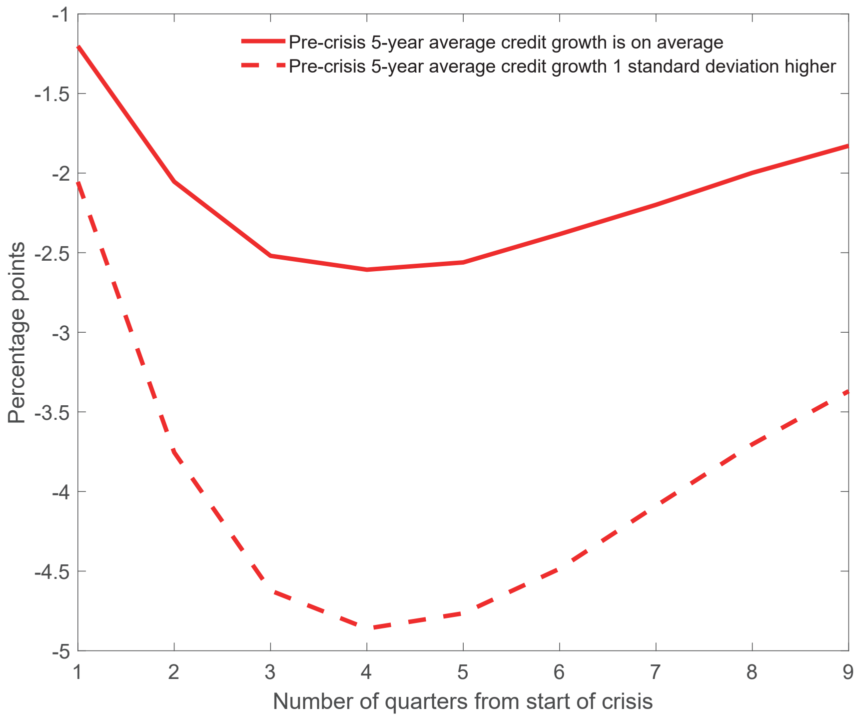


Figure 4. : Dynamics of output gap during financial crises

of the crisis (given that the average duration of a crisis is two years). This is consistent with the notion that recoveries from financial crises are very slow due to the scarring effects of such crises on the real economy.

The probability of a crisis start

The probability of being in a crisis episode is given by a Markov process, which is determined by the probability of a crisis starting and the duration of the crisis. We assume a crisis duration of eight quarters, which reflects the average unfiltered peak-to-trough duration of the financial cycle in Europe as defined in Schüler, Hiebert and Peltonen (2015).

The probability of switching from normal times to the crisis regime, p_C, is given by the linking function and the probability of returning from the crisis regime to the normal regime is p_N.

We describe the estimated logistical regression for the probability of a crisis starting in section II.B. The quarterly probability of a crisis start is a logistic function that links the growth in real private credit, real house prices to disposable

Table 3—: Markov transition probabilities

From / To	Normal times	Crisis times
Normal times	$1 - p_{C,t}$	$p_{C,t}$
Crisis times	p_N	$1 - p_N$

income, real equity prices, and the change in real interest rate to the probability of a crisis start.[24] We basically use the first column of Table 2 to incorporate the estimated probability of crisis function into our regime-switching DSGE model.[25] In particular, our (quarterly) probability of a crisis start, $p_{C,t}$, is given by:

(64)

$$p_{C,t} = 1 - \frac{1}{1 + \exp(-5.444 + 0.266 B_t^{5y} + 0.034 Q_t^{K,3y} + 0.128 \frac{P_t^H}{Y_t}^{5y_t} + 0.745 \Delta r_t^{3y})}$$

where B_t^{5y} is five-year average growth in real private credit, $Q_t^{K,3y}$ is three-year average growth in real equity prices, $\frac{P_t^H}{Y_t}^{5y_t}$ is five-year average growth in house price to disposable income, and Δr_t^{3y} is the three-year average change in real interest rate.

Figure ?? plots the annualised crisis probability as a function of its inputs. The probability of a crisis start increases from 1.72% to 1.85% when five-year average real private credit growth is 30% higher.[26] Similarly, the probability of a crisis starting increases from 1.72% to 1.85% when the three-year average real interest rate is 10% higher. This probability increases from 1.72% to 1.8% (1.74%) if the real five-year average growth in house price to disposable income (real three-year equity price growth) is 30% higher. Overall, real private credit growth and changes in real interest rates are the key factors driving the probability of a crisis, followed by real house and equity prices.

IV. Calibration and Estimation of the Model

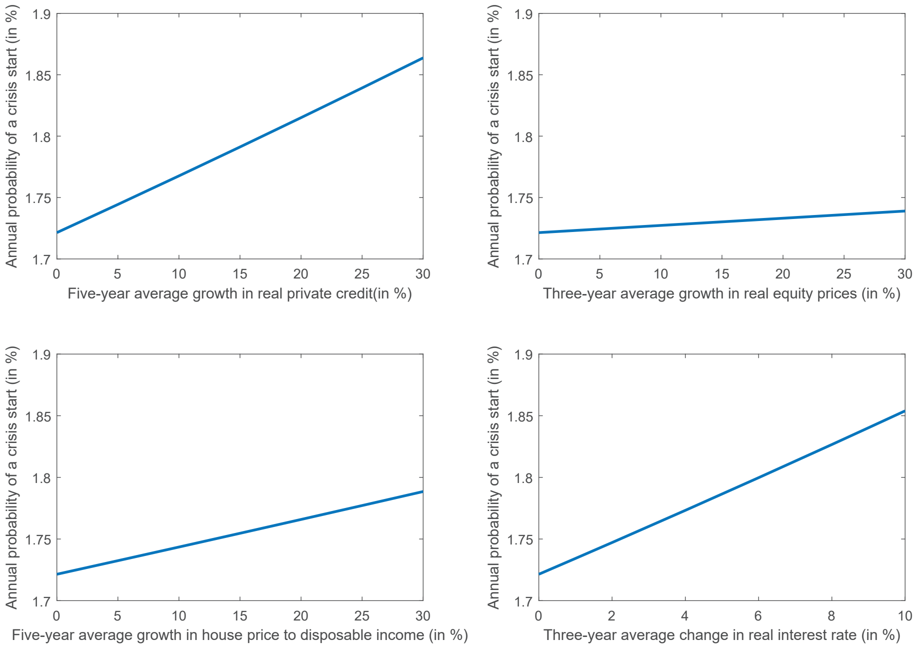
We calibrate the parameters that pin down the steady state of the model to match several macroeconomic and financial ratios in the euro area data. We

[24]See Ajello et al. (2019) and Gerdrup et al. (2017) for other examples where they use household credit growth as a proxy for crisis severity and probability.

[25]We use the link function described above with one important modification. When we simulate the model, we truncate the probability of a crisis starting so that the economy does not enter a crisis if any of the inputs of the logistic function is below zero. Hence, in order to match the estimated long-run annual probability of crisis starting at 1.7% on average in our model while truncating the probability of crisis, we recalibrated the constant term in the estimated logit function used in the model and set it at -4.725 instead of using the estimated constant of -5.444.

[26]Svensson (2017) estimated an annualized probability of a crisis start of 3.2% based on a linking function using a database of 14 developed countries for 1870-2008 (?).

Figure 5. : Crisis probability function



then estimate the remaining dynamic parameters of the model using Bayesian techniques, as in An and Schorfheide (2007). The computations are performed using the *RISE* toolbox[27]. In the following sections, we describe the data used for estimation, give an account of how the steady state of the model is calibrated, and report our prior and posterior distributions in the Bayesian estimation of the model.

A. Data

We use 15 observables for the estimation of the model. The macroeconomic and financial times series used cover euro area wide variables. Real variables include GDP, consumption, business investment, residential investment, and government expenditures. Financial variables include real household and business credit, real deposits, real house and equity prices, household and business lending rates, and deposit rates. Nominal variables are price inflation, wage inflation, and the policy

[27] "Rationality In Switching Environments" (*RISE*), an object-oriented Matlab toolbox for solving and estimating nonlinear regime-switching DSGE models. The toolbox was developed by Junior Maih and is freely available for download at https://github.com/jmaih/RISE_toolbox.

rate. The data source is Eurostat. The data for the real variables are in constant prices from the national accounts, whereas credit, house, and equity prices are deflated by consumer prices. The sample period is 1999Q1-2019Q4. Data with a trend are made stationary using the HP filter (smoothing parameter equal to 1,600), while all interest and inflation rates are demeaned. Figure 6 plots the transformed data.

B. Calibration of the steady-state

We calibrate the steady state of the model by matching several real and financial "great ratios" in the euro area for the sample period from 1999 to 2019. Specifically, we aim to match 5 macroeconomic aggregates and 7 financial targets. Table 4 lists the empirical ratios and the model's steady-state counterparts.

Table 4—: Data targets and steady-state calibration values

Target	**Data**	**Steady state**
Macroeconomic aggregates		
Consumption to GDP	0.58	0.58
Corporate investment to GDP	0.15	0.15
Housing investment to GDP	0.06	0.06
Government spending to GDP	0.21	0.21
Housing capital to GDP	1.27	1.27
Financial sector		
Household lending to total assets	0.34	0.34
Business lending to total assets	0.66	0.66
Bank capital to total assets	0.10	0.10
Total assets to GDP	1.18	1.18
Average annual business credit spread (%)	2.67	2.67
Average annual household credit spread (%)	2.75	2.75
Average annual funding spread (%)	0.64	0.64
Average annual deposit rate (%)	2	2

We set the household discount factor, β_P to 0.8789 to match the average annual deposit rate of 2%. The calibrated discount factor parameter is lower than the existing literature as the model explicitly features households' preferences for deposits in the utility function. The elasticity of substitution for labour services of patient and impatient households, ν^p and ν^p are calibrated to 5.76 and 11.15 to have hours worked one-third of the time.

We set the quarterly physical capital and housing capital depreciation rates, δ_H and δ_K, to match business and residential investment to GDP ratios of 15% and

6% in the data. We use the utility parameter for housing, j, to obtain a housing capital-to-GDP ratio of about 127%.

We assume the final good as the model's numéraire good and accordingly set the price of this good to 1. The price of the intermediate good is also set to 1 in the steady state. Although markups have shown an increasing trend over the world, as many studies show, we set the elasticity of substitution between goods, ϵ^y, to 6 to obtain a markup of 1.2 (20 %), and calibrate the capital share parameter in the production function, α, to 0.25, following similar calibrations in the literature.

We set the inflation target to 2%, although the average inflation rate might differ from the ECB's inflation target over the sample period. The nominal policy rate is calibrated to be 2.5%. Parameters that pin down interest rate markups in the banking sector are set to match credit spreads (difference between lending rates and policy rates) from the data. In particular, we set the elasticity of substitution parameters, ϵ^{bh} and ϵ^{be}, to 1.79 and 1.76, to match annual household and business loan spreads of 2.75% and 2.67%, on average. We also calibrate the elasticity of substitution between deposit services, ϵ^d, to 0.77 to obtain an annual average funding spread (difference between policy and deposit rates) of 64bps.

We use steady-state housing and entrepreneurial collateral constraint parameters, ϕ^H_{ss} and ϕ^E_{ss} to match housing lending to GDP ratio of 40% and business lending to total asset ratio of 66%. Following capital regulations in the euro area, we set capital requirements for banks to 10%, of which 2% is the countercyclical capital buffer.

C. Estimation of dynamic parameters

We estimate 47 parameters, of which 16 are dynamic non-shock parameters, 16 are standard errors of structural shocks, and finally, 15 are their AR(1) persistence parameters. We use two types of priors in estimating the model, namely system priors, to discipline some model moments and marginal priors, which we explain below.

D. Choice of priors

We take a mixed approach to setting the marginal priors. We use the existing literature, empirical analysis, and comparable models for some parameters to find appropriate prior values. In addition, for some parameters, we set the prior means to match the targeted model moments below with the help of system priors. Finally, as the model is used for scenario and policy analysis, some priors are set based on assessments and judgments of model users and sector experts about model properties, including impulse responses to specific shocks and correlation patterns. Table 6 shows the marginal priors and posterior modes.

We choose a beta distribution for the consumption habit persistence parameter with a prior mean of 0.85 and a standard deviation of 0.05 due to the low consumption volatility observed in the data. We calibrate the parameters regarding house-price expectations and housing investment adjustment costs to match the volatilities of housing investment and household credit and to get empirically relevant effects of a monetary policy shock on house prices and housing investment. Similarly, we calibrate the prior mean on investment adjustment cost parameters to match investment volatility. As in Adolfson et al. (2013), we set the prior mean of the curvature parameter in the capital utilisation cost, ϕ_u, to 0.2 to allow for a varying degree of utilisation of the capital stock. Prior means for price and wage adjustment costs are calibrated to be broadly in line with the moments on price and wage inflation rates, but prior standard deviations are set to give room for flexibility in the estimation.

In the banking sector, we estimate the adjustment costs related to changing the deposit, mortgage, and corporate lending rates. We calibrate the prior means to match observed interest pass-through in the euro area data, i.e., close to 1-to-1 for deposit rates and 1-to-0.8 for corporate and household lending rates.

Table 5—: Standard deviations of data vs. model variables (%)

Variable	Data	Model
Real variables		
Output	2.07	2.07
Consumption	1.98	1.98
Business investment	4.01	4.01
Housing investment	3.38	3.38
Government spending	0.74	0.74
Financial variables		
Household credit	1.28	1.28
Business credit	1.98	1.98
Deposits	1.20	1.20
Real house prices	1.25	1.25
Household lending rate	0.95	0.95
Corporate lending rate	1.40	1.40
Deposit rate	1.36	1.36
Nominal variables		
Price nflation	0.98	0.98
Wage inflation	0.77	0.77
Policy rate	1.53	1.53

The standard deviations of model-implied gaps of the observable variables are computed at the posterior mode.

The *RISE* toolbox allows for augmenting marginal priors (below) with *system priors*.[28] In contrast to marginal priors that deal with parameters independently, system priors are priors about the model's features and behaviour as a system and are modeled with a density function conditional on the model parameters. Theoretically, the system priors can substitute or be combined with marginal priors. In our estimation setup, we choose to augment our marginal priors with specific beliefs about the variances of the observed variables. Specifically, we specify our system priors as inverse gamma distributions over the variances of the observed variables, $N(\mu, \sigma)$, where we set μ equal to the second-order moment from the data that is used in the estimation, and σ is set to 10% of the mean. We did not set prior beliefs about co-variances. The standard deviations of the observables are listed in Table 5.

The model features 16 structural shocks, equal to the number of observable variables. All shocks are assumed to follow first-order autoregressive processes, except for the monetary policy shock, which is a pure innovation. Hence, there are 16 persistence parameters.

Following Gerali et al. (2010), all shocks are assumed to have an inverse gamma distribution with a prior mean of 0.01 and a prior standard deviation of 0.05. The persistence parameters are given a beta distribution with a prior mean of 0.8 and a standard deviation of 0.1.

E. Posterior results

Table 6 shows the estimation results, including the prior distribution and the posterior modes of the estimated model parameters.

Habit persistence in consumption turns out to be 0.89 after the estimation, showing a considerable degree of inertia in consumption. The posterior mode of the share of households with hybrid house price expectations is 0.07, smaller than the prior. This could be due to the fact that we did not have any particular house price expectations data at the household level during the estimation, which could be more informative for this parameter.

The Rotemberg-type price adjustment cost parameter is estimated to be around 52, which is not far away from the prior mean, while the wage adjustment cost parameter turns out to be 97.1, showing substantial persistence in wages. Inflation indexation to past inflation is estimated at 0.66, which is highly backward-looking, while wage inflation indexation is 0.18, much lower than its prior mean, which could also be due to the higher estimated wage adjustment cost parameter.

The posterior mode estimates of interest rate adjustment costs in the banking sector suggest that the pass-through from the policy rate to household lending rates is slower than that to corporate lending rates. Banks appear to adjust corporate lending rates more quickly than household lending rates. On the deposit

[28] This is somewhat similar to the framework laid out in Andrle and Benes (2013) and Del Negro and Schorfheide (2008). See the *RISE* website (`https://github.com/jmaih/RISE_toolbox`) for the particular codes.

side, the estimate suggests a higher pass-through from the policy rate to the deposit rate than the initial prior mean.

On the monetary policy rule side, the interest rate smoothing parameter is estimated at 0.65, which is lower than the prior mean, implying a low degree of policy inertia in the interest rate rule. On the other hand, the inflation response coefficient is higher than its prior mean, reflecting the ECB's strong price stability mandate. Although lower than the prior mean, the response coefficient to output is also significant, reflecting the central bank's concern for output stability, but less so compared to the price stability mandate.

Table 6—: Marginal prior and posterior distributions

			Prior		Posterior
		Distr.	Mean	S.d.	Mode
Dynamic parameters					
b^c	Habit persistence in consumption	β	0.8	0.05	0.89
b^{sa}	Share of households with hybrid house price expectations	β	0.3	0.05	0.07
λ^{sa}	Degree of backward-lookingness in house price expectations	β	0.35	0.05	0.35
κ^P	Price adjustment costs	Γ	50	20	51.9
ϕ^W	Wage adjustment costs	Γ	50	20	97.1
ι_p	Inflation indexation	Γ	0.5	0.15	0.66
ι_W	Wage inflation indexation	Γ	0.5	0.15	0.18
κ_i	Business investment adjustment costs	Γ	2.5	1	10.8
κ_h	Housing investment adjustment costs	Γ	2.5	1	6.63
κ^d	Deposit rate adjustment costs	Γ	10	2.5	4.92
κ^{be}	Business lending rate adjustment costs	Γ	3	2.5	5.37
κ^{bh}	Household lending rate adjustment costs	Γ	6	2.5	15.23
κ^{kb}	Cost of deviating from regulatory capital requirements	Γ	10	5	4.48
ρ^r	Interest rate smoothing	β	0.75	0.1	0.65
ϕ^π	Response coefficient to inflation	Γ	2	0.1	2.23
ϕ^y	Response coefficient to output	Γ	0.5	0.05	0.24
Shock persistence					
ρ_u	Consumption preference shock	β	0.8	0.1	0.38
ρ_g	Government spending shock	β	0.8	0.1	0.82
ρ_j	Housing preference shock	β	0.8	0.1	0.86
ρ_d	Shock to household savings	β	0.8	0.1	0.89
ρ_{qh}	Housing investment efficiency shock	β	0.8	0.1	0.31
ρ_{qk}	Business investment efficiency shock	β	0.8	0.1	0.10
ρ_{z^L}	Temporary TFP shock	β	0.8	0.1	0.47
ρ_{mi}	Shock to household LTV ratio	β	0.8	0.1	0.96
ρ_{me}	Shock to business LTV ratio	β	0.8	0.1	0.68
ρ_p	Price markup shock	β	0.8	0.1	0.97
ρ_w	Wage markup shock	β	0.8	0.1	0.52
ρ_{be}	Shock to business lending rate	β	0.8	0.1	0.56
ρ_{bh}	Shock to household lending rate	β	0.8	0.1	0.24
ρ_d	Shock to household deposit rate	β	0.8	0.1	0.76
ρ_{kb}	Shock to bank capital	β	0.8	0.1	0.12
Shock standard deviations					
σ_u	Consumption preference shock	Γ	0.01	0.05	0.05
σ_g	Government spending shock	Γ	0.01	0.05	0.006
σ_j	Housing preference shock	Γ	0.01	0.05	0.008
σ_d	Shock to household savings	Γ	0.01	0.05	0.02
σ_{qh}	Housing investment efficiency shock	Γ	0.01	0.05	0.01
σ_{qk}	Business investment efficiency shock	Γ	0.01	0.05	0.03
σ_{z^L}	Temporary TFP shock	Γ	0.01	0.05	0.01
σ_{mi}	Shock to household LTV ratio	Γ	0.01	0.05	0.004
σ_{me}	Shock to business LTV ratio	Γ	0.01	0.05	0.044
σ_p	Price markup shock	Γ	0.01	0.05	0.005
σ_w	Wage markup shock	Γ	0.01	0.05	0.204
σ_{be}	Shock to business lending rate	Γ	0.01	0.05	0.19
σ_{bh}	Shock to household lending rate	Γ	0.01	0.05	0.58
σ_d	Shock to household deposit rate	Γ	0.01	0.05	0.02
σ_{kb}	Shock to bank capital	Γ	0.01	0.05	0.08
σ_r	Monetary policy shock	Γ	0.01	0.05	0.001
σ_Y	Output measurement error	Γ	0.01	0.05	0.006

V. Quantitative Properties of the RS-DSGE Model

In this section, we describe the quantitative features of the RS version of our DSGE model, including the nature of the financial cycles and financial crises within the model simulations. These properties of the model make it suitable for conducting structural macro-financial risk analysis and assessing monetary and macroprudential policies.

A. *Prolonged financial cycles*

It is widely documented in the literature that financial cycles are more long-lasting than business cycles (Claessens, Kose and Terrones, 2012; Claessens et al., 2013; Drehmann, Borio and Tsatsaronis, 2012). Household debt and house prices are more persistent than standard macro variables like output, and expectations play a crucial role in driving prolonged financial cycles (Gelain, Lansing and Natvik, 2018).

Figures 7 and 8 display the simulations of real house prices and household credit in the model with and without hybrid house price expectations. In the latter, we set the share of agents with partially backward-looking house price expectations, $back_sa$, to zero, implying that all the economic agents have model-consistent, rational expectations about house prices. In the model with hybrid house price expectations, the share of agents with partially backward-looking house price expectations is set at 0.35.

The figures show that given the same set of structural shocks hitting the economy over the business cycle, the baseline model with hybrid house price expectations generates endogenously more long-lasting and more volatile cycles in main financial variables such as house prices and household debt compared to the model with rational, forward-looking house price expectations. The baseline model with hybrid expectations does not need to rely on persistent structural shocks to generate prolonged boom episodes as in the actual data.

B. *Dynamics of financial crises*

Figure 9 shows the distribution of the behaviour of the main macroeconomic and financial variables when the economy enters into a crisis. We simulate the model for 1,000,000 periods and collect the dynamics of the variables of interest in the crisis regime. We obtain 4326 crisis episodes with an average duration of 7.9 quarters each and produced the fan chart below. The black dashed lines display the median behaviour while the other shaded areas show the 30th, 50th, 70th, and 90th percentiles. We obtain this distribution of different variables during crisis episodes since different pre-crisis real credit growth rates, hence the financial imbalances, lead to different severity for each crisis period.

The economy is hit by asymmetrically large crisis shocks based on the domestic financial crisis narrative derived from estimated local projections of key macro-financial variables. We use shocks to household and corporate credit spreads, housing preferences, household savings via deposits, and shocks to household and business LTV ratios, in addition to estimated standard business cycle shocks when a financial crisis unfolds.

The sharp widening of household and corporate credit spreads by around 120bps and 70bps, respectively, combined with tighter lending standards, leads to a sharp fall in household and corporate credit of around 30% and 7%, respectively. The fall in household credit is exacerbated by a fall in household demand for housing loans as households' disposable income falls and they substitute housing services for consumption. The fall in housing demand leads to a fall in house prices of 8%. The reduction in credit supply translates into a fall in residential and business investment of around 16%. Moreover, the fall in consumption is cushioned by the drawdown of household savings, limiting its decline compared to the fall in output. Therefore, the median fall in output is around 2.5%. In the least severe crisis, output falls by about 0.4% at the peak, while it declines by around 6% in the most severe crisis. Depending on the severity, consumption, business and housing investments could fall by 3.5%, 35%, and 37%, respectively.

C. *Model moments under different regimes*

Table 7 displays the second moments of some selected model variables and annualised frequencies of crisis for the models with and without crisis.

Table 7—: Model moments with and without crisis

Volatilities (%)	Crisis	No-crisis	Percent change
Output	1.95	1.78	9.5
Consumption	1.84	1.75	5.1
Residential investment	9.90	6.87	44.1
Business investment	9.10	7.61	19.5
Household credit	11.5	9.70	18.5
Business credit	5.01	4.03	24.3
Real house prices	3.14	2.36	33.0
Prob. of crisis start (Ann. %)	1.73	0.00	–

Notes*: Model standard deviations and the frequency of financial crises are computed from 1,000,000 simulations.*

The results indicate that incorporating financial crises into the model increases the volatilities of macroeconomic and financial variables, as expected. The crisis regime has the largest effect on residential investment and house prices, followed by business credit and business investment.

VI. Policy Applications

In this section, we present some counterfactual exercises and policy applications around the Global Financial Crisis to show how the model framework can be used to conduct structural macro-financial risk analysis.

We start with the period from end-2003 to end-2011, including the boom and bust episodes around the GFC. We first use the regime-switching DSGE model to filter out the structural shocks that replicate the dynamics of key macroeconomic and financial aggregates, including the GFC happening in 2008:Q3 (Figure 10). All variables are expressed in percentage deviation from their steady-state values, hence in gap forms, except inflation and interest rates, plotted in levels. We normalise the variables in gap forms, assuming they were at zero in 2003:Q4.

We then feed those structural shocks into the model to perform our counterfactual analyses of the economic environment and policy settings before and after the GFC.

A. *Housing booms and house price expectations*

Partially backward-looking house price expectations play a relevant role in generating boom-bust episodes in many key macroeconomic and financial variables in our model. With these hybrid expectations, economic agents project that past values of house prices are good predictors of future prices, leading to waves of overoptimism or overpessimism and thus generating long-lasting financial cycles, as in the actual data. We conduct such an experiment of overoptimism in house prices in Figure 11.

Figure 11 shows how selected variables would have performed around the GFC if house price expectations were more backward-looking, i.e. deviating more from rational expectations. The implication is that economic agents, having observed house prices rising in the past, expect house prices to rise in the future. In this case, the same set of structural shocks hitting the economy leads to a more pronounced boom, especially in residential investment. Household credit and house prices would have risen more than in the baseline, leading to higher consumption and output. In addition, the economic downturn induced by the financial crisis is more severe and prolonged than in the baseline, as late recovery in house prices also delays the rebound in output and consumption.

B. *Banks' lending standards: Data vs. Model*

During the GFC, there is vast evidence that banks tightened their lending standards considerably compared to the pre-GFC episode. Given this fact, we conduct an experiment where we compare the change in household lending standards for house purchases to the change in the model-implied household loan-to-value (LTV) ratio. For the former, we use the ECB's Bank Lending Survey, which reports the percentage of senior loan officers that expect a tightening in credit standards for house purchase loans in the next three months.

Figure 12 displays the evolution of household lending standards and the inverse of the model-implied LTV ratio for households. The figure shows that credit standards are pretty loose before the GFC in the data, and the model broadly captures this with higher household LTV ratios. When the crisis hit in 2008:Q3, banks sharply tightened their lending standards, which the model is able to explain with a sharp decline in the LTV ratio for households. After the peak, with the help of macroprudential policies put in place, banks started to loosen credit standards faster than the model-implied version, as we did not explicitly incorporate looser macroprudential regulations after the GFC in this exercise. Overall, we can conclude that the model is able to explain successfully the change in credit conditions as observed in the data.

C. *Leaning-against-the-wind type monetary policy*

It has long been argued that central banks should consider financial imbalances in their monetary policy decisions and raise interest rates above the levels implied by their mandates despite the likely economic costs. Leaning-against-the-wind (LAW)-type monetary policy has been one of the most contentious issues discussed by academics and central bankers for more than two decades. Proponents of LAW-type monetary policy emphasise the increased financial vulnerabilities following the loose monetary policy stance in most major economies in response to the Global Financial Crisis (GFC) and the COVID-19 pandemic, thereby sowing the seeds of the next financial crisis. On the other hand, the prevailing view against LAW is that the costs of implementing it far outweigh the benefits. The lost output and missed inflation target in normal times due to LAW outweigh the potential benefits of a less likely and less severe financial crash. Given these opposing views, we conduct a policy experiment in our framework in which the central bank keeps the policy rate 100bps higher than the pre-crisis monetary policy rule implied.

Figure 13 shows that LAW-type monetary policy would have mitigated the rise in house prices and household credit before the GFC as expected, albeit to a limited extent. On the other hand, it leads to a much lower output and consumption in addition to a lower inflation rate, missing the target before the GFC. When we look at the recovery episode, we see the benefits of LAW in terms of faster recovery in output, residential and business investment as well as house prices and household credit. Overall, answering the question of whether the benefits exceed the cost of implementing LAW requires a careful welfare analysis, which is currently beyond the scope of the paper but an interesting avenue to explore.

D. *Macroprudential policies around Global Financial Crisis*

Macroprudential policy has been at the forefront of the policy debate in the aftermath of the GFC. It has been widely argued that financial conditions were too loose at the onset of the financial crisis, leading to a pronounced rise in house prices and household debt. Bank capital regulation is one of the key macroprudential policy tools that began to be revised immediately after the GFC, and is one of the main pillars of the Basel III Accord. Taking stock of these developments, we conduct a macroprudential policy exercise to assess whether bank capital requirements were not sufficiently restrictive to address the loose credit conditions prior to the GFC. In particular, we study how the key macro and financial variables would have evolved if capital requirements had been 2 percentage points higher.

Figure 14 shows that the increase in household credit before the GFC would have been much more subdued than in the baseline, and household lending rates would have been higher as banks need to retain more capital to meet the requirements, increasing the cost of funding. Therefore, the increase in house prices and residential investment would have been limited. As the collateral value of housing would have been lower due to less pronounced house prices, consumption and output would have been lower prior to the crisis. Overall, tighter capital requirements would have led to more prudent lending to households, mitigating the housing boom as expected.

A more subdued housing market would have limited financial imbalances, resulting in a much less severe financial crisis. The decline in house prices, residential investment, consumption, and output would have been muted relative to the baseline. Moreover, the recovery from the crisis would have been much faster. Comparing the decline in output and consumption before the crisis with the faster recovery episode relative to the baseline, we can conclude that sufficiently restrictive capital requirements would have been beneficial for the whole economy. A counterfactual exercise using LTV restrictions to limit credit imbalances before the GFC leads to similar conclusions.

We also emphasise policy complementarities between monetary and macroprudential policies in this exercise. If capital requirements had been higher before the crisis, monetary policy would not have needed to be as restrictive as in the baseline as both the rise in inflation and output would have been less pronounced. Therefore, monetary policy could have focused on maintaining price stability while macroprudential policy could have helped to contain financial stability risks.

Another interesting exercise is to compare implementing higher capital requirements vs. conducting LAW-type monetary before the GFC as in Figure 15. The results show that although the costs of implementing these two policies are comparable in terms of output loss before the crisis, the crisis is less severe and the recovery is much faster in the case of using higher capital requirements. The model offers interesting trade-offs about the complementarities between these two policy instruments.

E. Fiscal policy during the GFC

One of the policy discussions after the GFC was that there was not enough fiscal stimulus to reduce the severity of the crisis and speed up the recovery. For example, during the pandemic, advanced economies undertook large fiscal expansions that prevented a complete collapse of the global economy. In this section, we analyse such a fiscal stimulus package that increases government spending by 5 percentage points as a share of output. The size of this package is similar to the Next Generation EU (NGEU) program announced by the European Commission during the pandemic.

Figure 16 displays the evolution of key macro variables both in the baseline and in the counterfactual with fiscal stimulus. As expected, the economic downturn would have been much less severe with a limited impact of inflation, and the recovery phase would have been faster compared to the baseline. Finally, we note that we did not take into account the impact of the fiscal stimulus package on future public finances, which might have negative repercussions, especially in high-debt economies. We leave it for future research.

VII. Concluding remarks

In conclusion, this paper illuminates the crucial linkages between financial imbalances, financial crises, and their effects on economic downturns in advanced economies. We developed a Markov regime-switching version of a canonical New Keynesian DSGE model by drawing inspiration from the past patterns observed in financial crises. This model takes into account the intricate dynamics of financial imbalances, extended financial cycles, and the amplification of economic fluctuations induced by financial crises.

Our empirical findings align with the stylised facts associated with financial crises, emphasising the role of real private credit growth, overvaluation of asset prices, and interest rate dynamics as precursors to these events. Our model captures the rare, nonlinear, and asymmetric nature of financial crises nested within typical business cycles by introducing endogenous Markov-regime switching and incorporating a logit specification derived from empirical analysis.

Our framework's key addition is the inclusion of a representation of financial imbalances throughout normal and crisis times. Using conditionally heteroskedastic shocks and regime-switching structural dynamic parameterisation, our model provides a sophisticated understanding of the enduring financial cycles observed in advanced economies.

The quantitative analysis shows that our model can replicate the essential stylised facts of financial crises while maintaining consistency with typical business cycle moments in the data. This enables us to conduct meaningful structural macro-financial analysis, allowing us to investigate various policy scenarios. Notably, our policy applications showcase the implications and trade-offs associated with various monetary and macroprudential policy trajectories, such as analysing long-run or countercyclical capital requirements and loan-to-value (LTV) ratio regulations.

Our proposed framework offers a valuable contribution to the field by providing an empirically plausible environment for conducting comprehensive structural macro-financial risk analysis. By bridging the gap between historical data and theoretical modeling, our approach facilitates a greater understanding of the intricate interplay between financial imbalances, crises, and policy responses in advanced economies. As policymakers navigate the challenges of maintaining financial stability, our model is useful for informed decision-making and risk assessment.

REFERENCES

Adolfson, Malin, Stefan Laséen, Lawrence Christiano, Mathias Trabandt, and Karl Walentin. 2013. "Ramses II - Model Description." Sveriges Riksbank Occasional Paper Series 12.

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone. 2019. "Vulnerable Growth." *American Economic Review*, 109(4): 1263–89.

Adrian, Tobias, Vitor Gaspar, and Francis Vitek. 2024. "A Medium-Scale DSGE Model for the Integrated Policy Framework." *International Journal of Central Banking*, 20(4): 1–123.

Aikman, David, Andrew G Haldane, and Benjamin D Nelson. 2015. "Curbing the credit cycle." *The Economic Journal*, 125(585): 1072–1109.

Aikman, David, Jonathan Bridges, Sinem Hacioglu Hoke, Cian O'Neill, and Akash Raja. 2019. "Credit, capital and crises: a GDP-at-Risk approach." Bank of England Working Papers 824.

Ajello, A., T. Laubach, D. Lopez-Salido, and T. Nakata. 2019. "Financial stability and Optimal Interest Rate Policy." *International Journal of Central Banking*, 15(1): 279–326.

Andrle, Michal, and Jaromir Benes. 2013. "System Priors; Formulating Priors about DSGE Models' Properties." International Monetary Fund IMF Working Papers 13/257.

An, Sungbae, and Frank Schorfheide. 2007. "Bayesian Analysis of DSGE Models." *Econometric Reviews*, 26(2-4): 113–172.

Anundsen, André K, Karsten Gerdrup, Frank Hansen, and Kasper Kragh-Sørensen. 2016. "Bubbles and crises: The role of house prices and credit." *Journal of Applied Econometrics*, 31(7): 1291–1311.

Babeckỳ, Jan, Tomáš Havránek, Jakub Matěj, Marek Rusnák, Kateřina Šmídková, and Bořek Vašíček. 2014. "Banking, debt, and currency crises in developed countries: Stylized facts and early warning indicators." *Journal of Financial Stability*, 15: 1–17.

Benigno, Gianluca, Andrew Foerster, Alessandro Rebucci, and Christopher Otrok. 2021. "Estimating Macroeconomic Models of Financial Crises: An Endogenous Regime-Switching Approach." Federal Reserve Bank of San Francisco Working Paper 2020-10.

Bernanke, B.S., M. Gertler, and M. Gilchrist. 1999. *The Financial Accelerator in a Quantitative Business Cycle Framework.* in "Handbook of Macroeconomics", J.B. Taylor and M. Woodford, Eds. North-Holland.

Borio, Claudio, and Philip Lowe. 2004. "Securing sustainable price stability: should credit come back from the wilderness?" BIS working paper 157.

Borio, Claudio, Philip Lowe, et al. 2002. "Assessing the risk of banking crises." *BIS Quarterly Review*, 7(1): 43–54.

Claessens, Stijn, M Ayhan Kose, and Marco E. Terrones. 2012. "How do business and financial cycles interact?" *Journal of International Economics*, 87(1): 178–190.

Claessens, Stijn, M. Ayhan Kose, and Marco E. Terrones. 2014. "What happens during recessions, crunches and busts?" *Economic Policy*, 24(60): 653–700.

Claessens, Stijn, M. Ayhan Kose, Luc Laeven, and Fabian Valencia. 2013. "Understanding Financial Crises: Causes, Consequences, and Policy Responses." CEPR Discussion Papers 9310.

Cloyne, James, Òscar Jordà, and Alan M Taylor. 2023. "State-dependent local projections: Understanding impulse response heterogeneity."

Dell'Ariccia, Giovanni, Deniz Igan, Luc Laeven, Hui Tong, Bas Bakker, and Jerome Vandenbussche. 2012. "Policies for macrofinancial stability: How to deal with credit booms." *IMF Staff Discussion Note*, 12(06).

Dell'Ariccia, Giovanni, Deniz Igan, Luc Laeven, Hui Tong, Nicolas Coeurdacier, and José Luis Peydró. 2016. "Credit booms and macrofinancial stability." *Economic Policy*, 31(86): 299–355.

Del Negro, Marco, and Frank Schorfheide. 2008. "Forming priors for DSGE models (and how it affects the assessment of nominal rigidities)." *Journal of Monetary Economics*, 55(7): 1191–1208.

Drehmann, Mathias, and Kostas Tsatsaronis. 2014. "The credit-to-GDP gap and countercyclical capital buffers: questions and answers." *BIS Quarterly Review.*

Drehmann, Mathias, and Mikael Juselius. 2012. "Do debt service costs affect macroeconomic and financial stability?" *BIS Quarterly Review September.*

Drehmann, Mathias, Claudio Borio, and Kostas Tsatsaronis. 2011. "Anchoring Countercyclical Capital Buffers: The Role of Credit Aggregates." *International Journal of Central Banking*, 7(4): 189–240.

Drehmann, Mathias, Claudio Borio, and Kostas Tsatsaronis. 2012. "Characterising the financial cycle: don't lose sight of the medium term!" BIS Working Paper 380.

Duca, Marco Lo, Anne Koban, Marisa Basten, Elias Bengtsson, Benjamin Klaus, Piotr Kusmierczyk, Jan Hannes Lang, Carsten Detken (editor), and Tuomas Peltonen (editor). 2017. "A new database for financial crises in European countries." European Central Bank Occasional Paper Series 194.

Eggertsson, Gauti B, and Paul Krugman. 2012. "Debt, deleveraging, and the liquidity trap: A Fisher-Minsky-Koo approach." *The Quarterly Journal of Economics*, 127(3): 1469–1513.

Fink, Fabian, and Yves S Schüler. 2015. "The transmission of US systemic financial stress: Evidence for emerging market economies." *Journal of International Money and Finance*, 55: 6–26.

Gelain, Paolo, Kevin J. Lansing, and Caterina Mendicino. 2013. "House Prices, Credit Growth, and Excess Volatility: Implications for Monetary and Macroprudential Policy." *International Journal of Central Banking*, 9(2): 219–276.

Gelain, Paolo, Kevin J. Lansing, and Gisle J. Natvik. 2018. "Explaining the Boom-Bust Cycle in the U.S. Housing Market: A Reverse-Engineering Approach." *Journal of Money, Credit and Banking*, 50(8): 1751–1783.

Gerali, Andrea, Stefano Neri, Luca Sessa, and Federico M. Signoretti. 2010. "Credit and Banking in a DSGE Model of the Euro Area." *Journal of Money, Credit and Banking*, 42(s1): 107–141.

Gerdrup, Karsten R., Frank Hansen, Tord Krogh, and Junior Maih. 2017. "Leaning Against the Wind When Credit Bites Back." *International Journal of Central Banking*, 13(3): 287–320.

Gilchrist, Simon, and Egon Zakrajšek. 2012. "Credit spreads and business cycle fluctuations." *American Economic Review*, 102(4): 1692–1720.

Gilchrist, Simon, Vladimir Yankov, and Egon Zakrajšek. 2009. "Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets." *Journal of Monetary Economics*, 56(4): 471–493.

Gourinchas, Pierre-Olivier, and Maurice Obstfeld. 2012. "Stories of the twentieth century for the twenty-first." *American Economic Journal: Macroeconomics*, 4(1): 226–265.

Hafstead, Marc, and Josephine Smith. 2012. "Financial shocks, bank intermediation, and monetary policy in a DSGE model." Unpublished.

Hubrich, Kirstin, and Robert J Tetlow. 2015. "Financial stress and economic dynamics: The transmission of crises." *Journal of Monetary Economics*, 70: 100–115.

Iacoviello, Matteo. 2005. "House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle." *American Economic Review*, 95(3): 739–764.

Jordà, Òscar. 2005. "Estimation and inference of impulse responses by local projections." *American Economic Review*, 95(1): 161–182.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor. 2013. "When Credit Bites Back." *Journal of Money, Credit and Banking*, 45(s2): 3–28.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor. 2016. "SOVEREIGNS VERSUS BANKS: CREDIT, CRISES, AND CONSEQUENCES." *Journal of the European Economic Association*, 14(1): 45–79.

Kim, Jinill. 2000. "Constructing and estimating a realistic optimizing model of monetary policy." *Journal of Monetary Economics*, 45(2): 329–359.

Kiyotaki, N., and J. Moore. 1997. "Credit Cycles." *Journal of Political Economy*, 105: 211–248.

Kravik, Erling M, Thore Kockerols, and Yasin Mimir. 2023. "Leaning against persistent financial cycles with occasional crises." ESM Working Papers 56.

Laeven, Luc, and Fabian Valencia. 2013. "Systemic banking crises database." *IMF Economic Review*, 61(2): 225–270.

Laeven, Luc, and Fabian Valencia. 2020. "Systemic banking crises database II." *IMF Economic Review*, 68: 307–361.

Lo Duca, Marco, Anne Koban, Marisa Basten, Elias Bengtsson, Benjamin Klaus, Piotr Kusmierczyk, Jan Hannes Lang, Carsten Detken, and Tuomas Peltonen. 2017. "A new database for financial crises in European countries." ECB Occasional Paper 194.

Mendoza, E. 2010. "Sudden stops, financial crises, and leverage." *American Economic Review*, 100(5): 1941–66.

Mendoza, Enrique G, and Vivian Z Yue. 2012. "A general equilibrium model of sovereign default and business cycles." *The Quarterly Journal of Economics*, 127(2): 889–946.

Mian, Atif, Kamalesh Rao, and Amir Sufi. 2013. "Household balance sheets, consumption, and the economic slump." *The Quarterly Journal of Economics*, 128(4): 1687–1726.

Reinhart, Carmen M, and Kenneth S Rogoff. 2008. "Is the 2007 US sub-prime financial crisis so different? An international historical comparison." *American Economic Review*, 98(2): 339–344.

Reinhart, Carmen M, and Kenneth S Rogoff. 2009*a*. "The aftermath of financial crises." *American Economic Review*, 99(2): 466–472.

Reinhart, Carmen M, and Kenneth S Rogoff. 2009*b*. *This time is different: Eight centuries of financial folly.* Princeton University Press.

Rotemberg, Julio J. 1982. "Sticky Prices in the United States." *Journal of Political Economy*, 90(6): 1187–1211.

Schularick, Moritz, and Alan M Taylor. 2012. "Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870–2008." *American Economic Review*, 102(2): 1029–1061.

Schüler, Yves S, Paul Hiebert, and Tuomas A Peltonen. 2015. "Characterising the financial cycle: a multivariate and time-varying approach." European Central Bank Working Paper No 1846.

Svensson, Lars E.O. 2017. "Cost-benefit analysis of leaning against the wind." *Journal of Monetary Economics*, 90: 193 – 213.

Yeyati, Eduardo Levy, and Ugo Panizza. 2011. "The elusive costs of sovereign defaults." *Journal of Development Economics*, 94(1): 95–105.

Figure 6. : Transformed data for the estimation

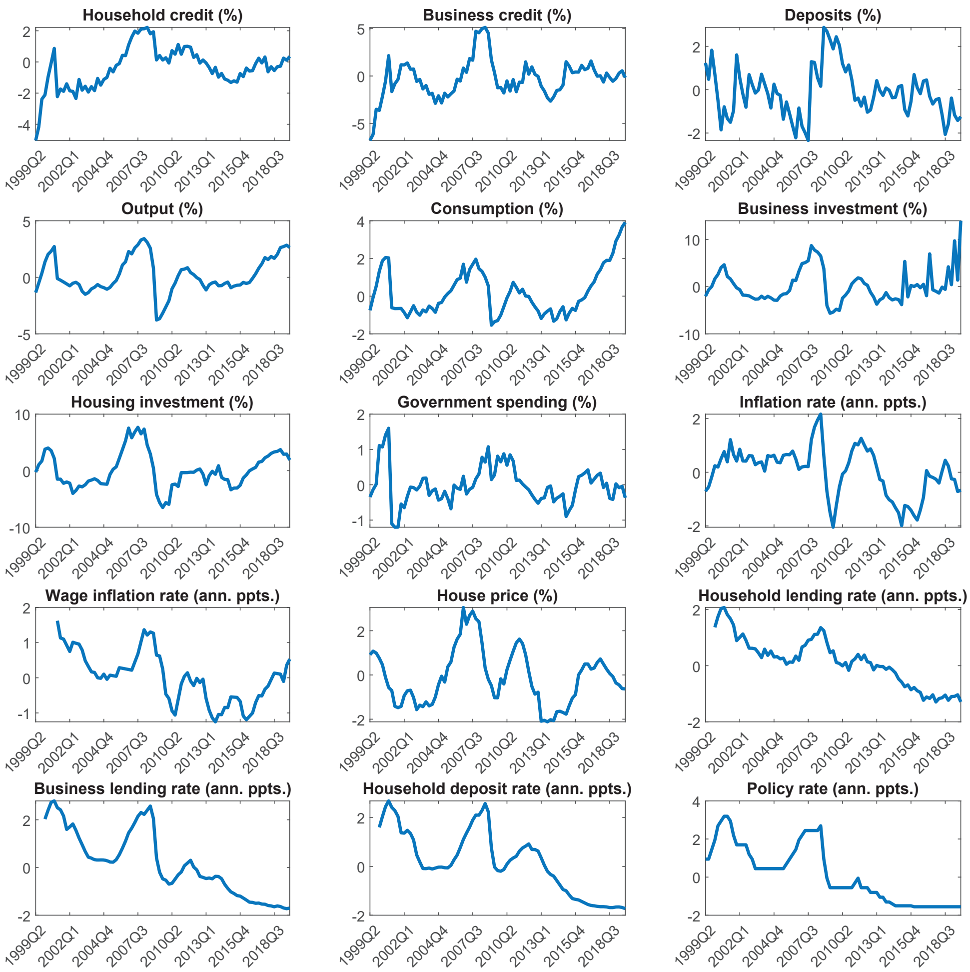


Figure 7. : House prices: Simulations in the models with and without hybrid house price expectations

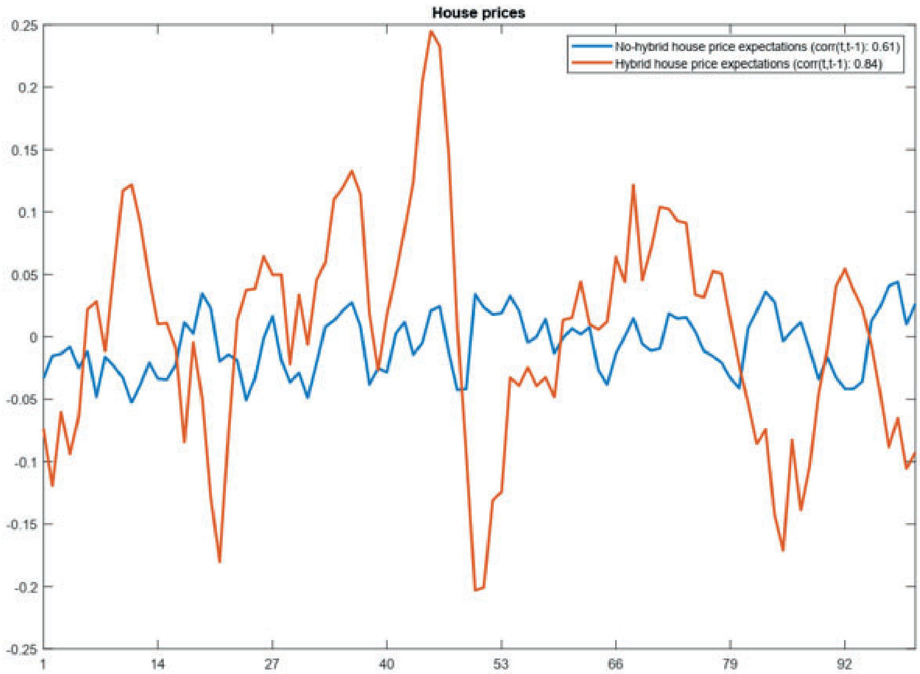


Figure 8. : Household debt: Simulations in the models with and without hybrid house price expectations

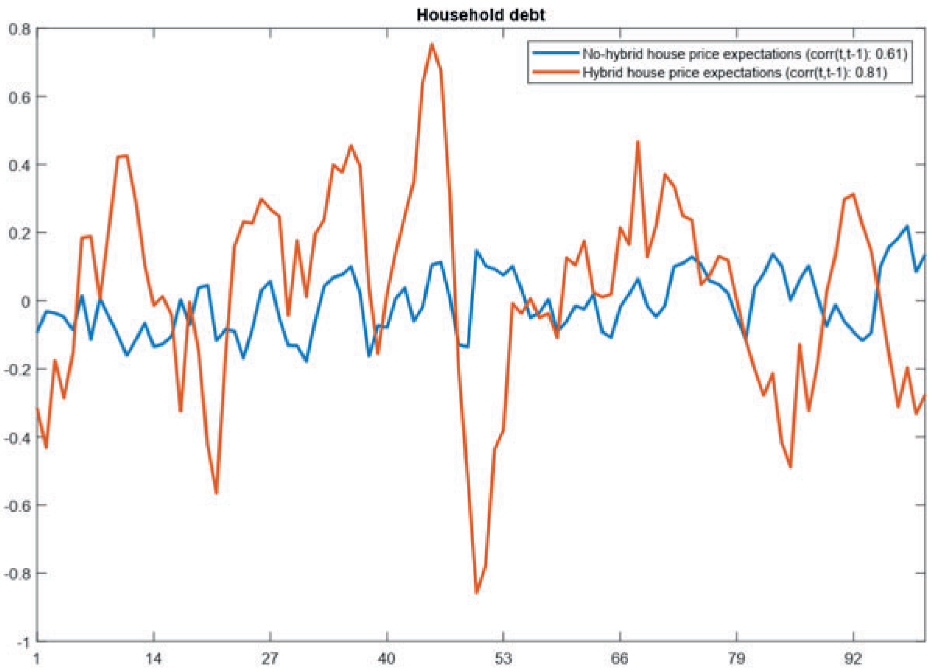


Figure 9. : Dynamics of key macro-financial variables during financial crises (in % level deviations)

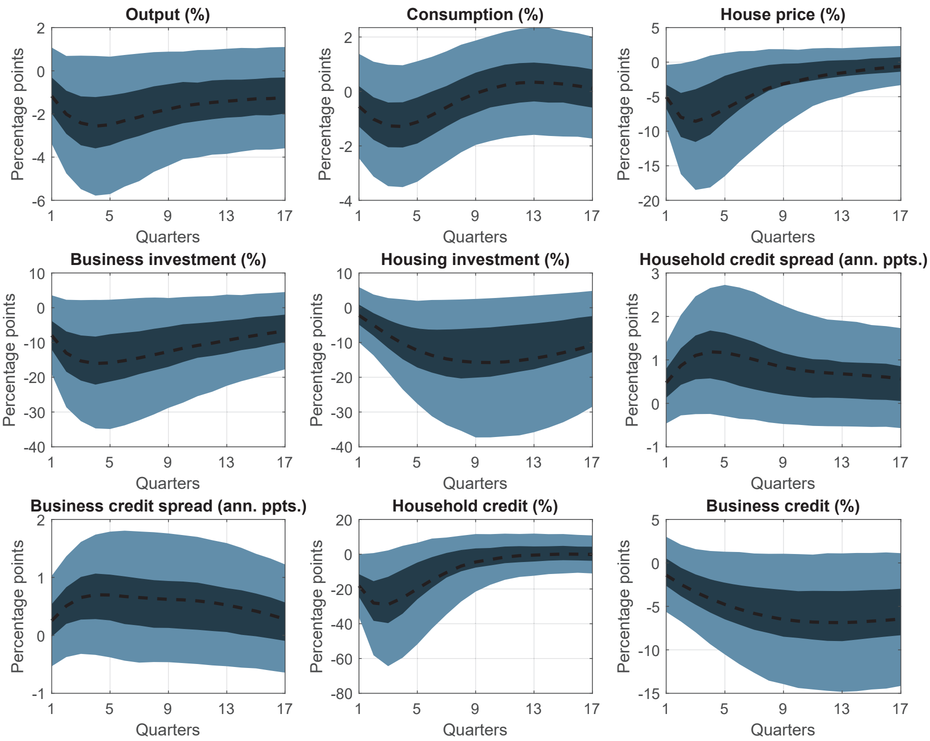


Figure 10. : Dynamics of key macroeconomic and financial variables around the GFC

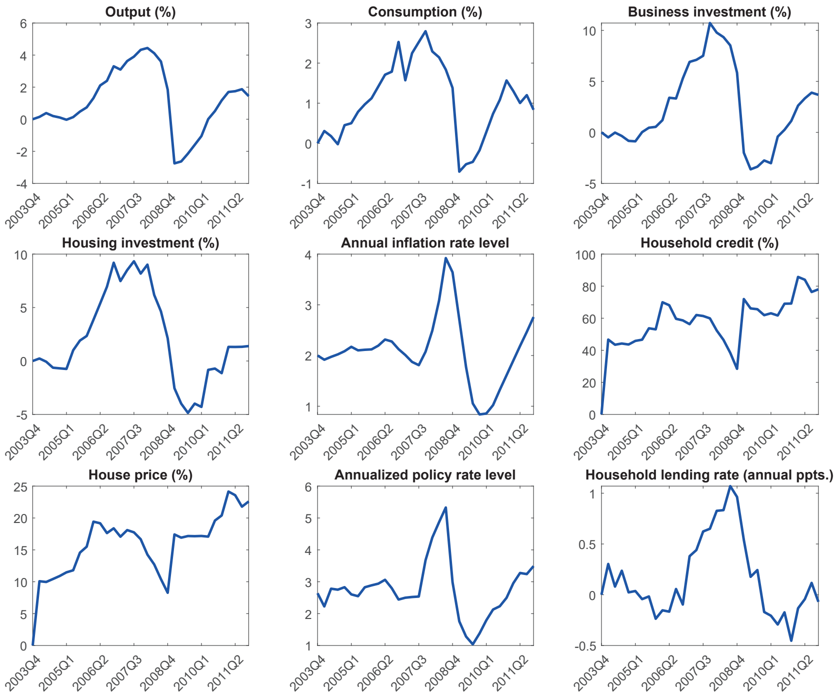


Figure 11. : The role of house price expectations in housing booms around the GFC

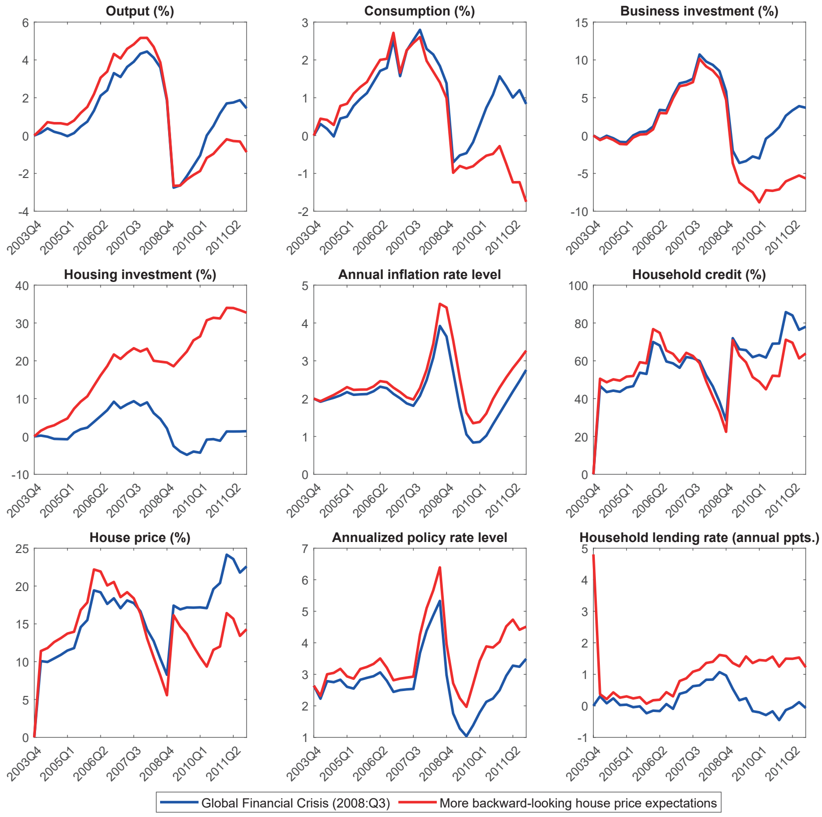


Figure 12. : Household lending standards around the GFC: Data vs. Model

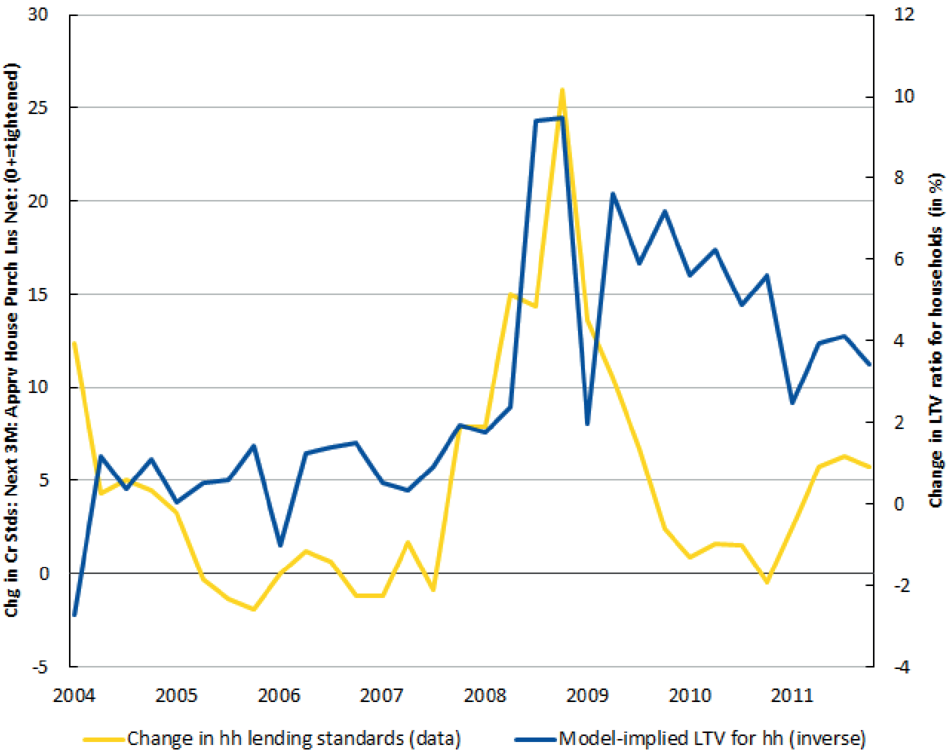


Figure 13. : Leaning-against-the-wind type monetary policy before the GFC

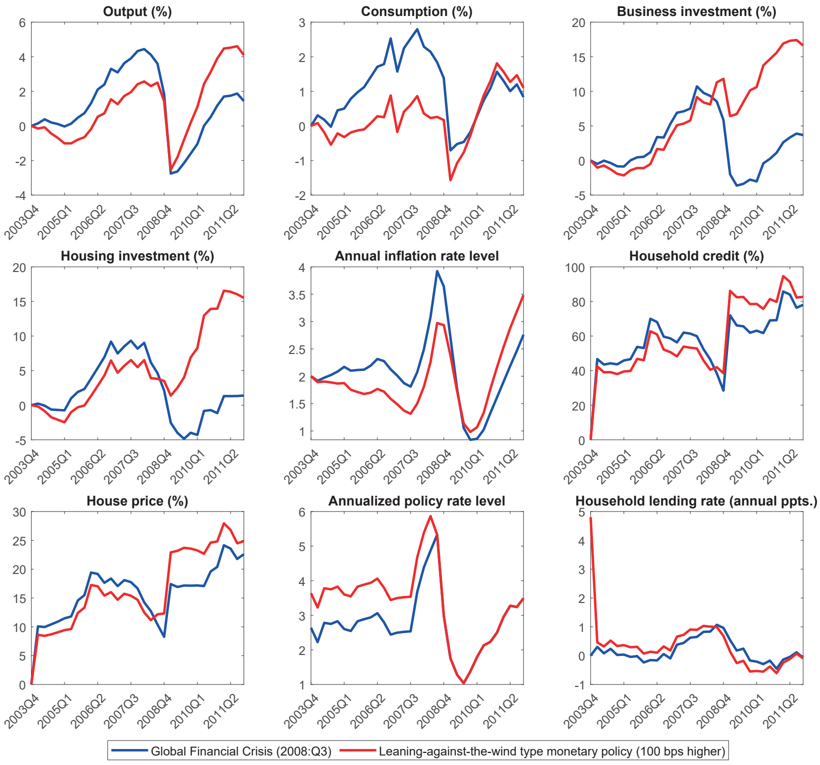


Figure 14. : Capital regulations and macroeconomic dynamics around the GFC

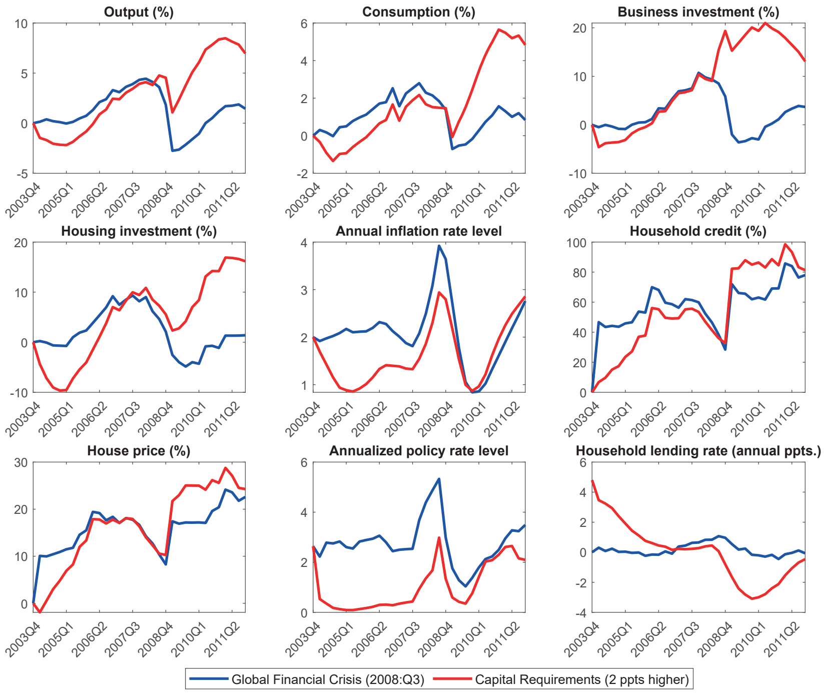


Figure 15. : Capital regulations and LAW around the GFC

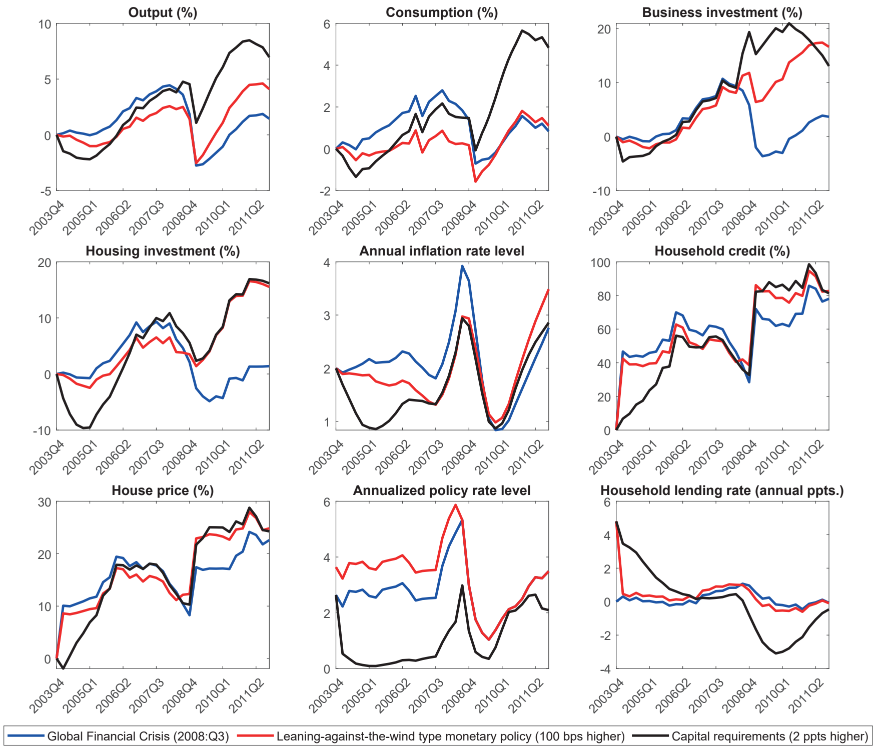
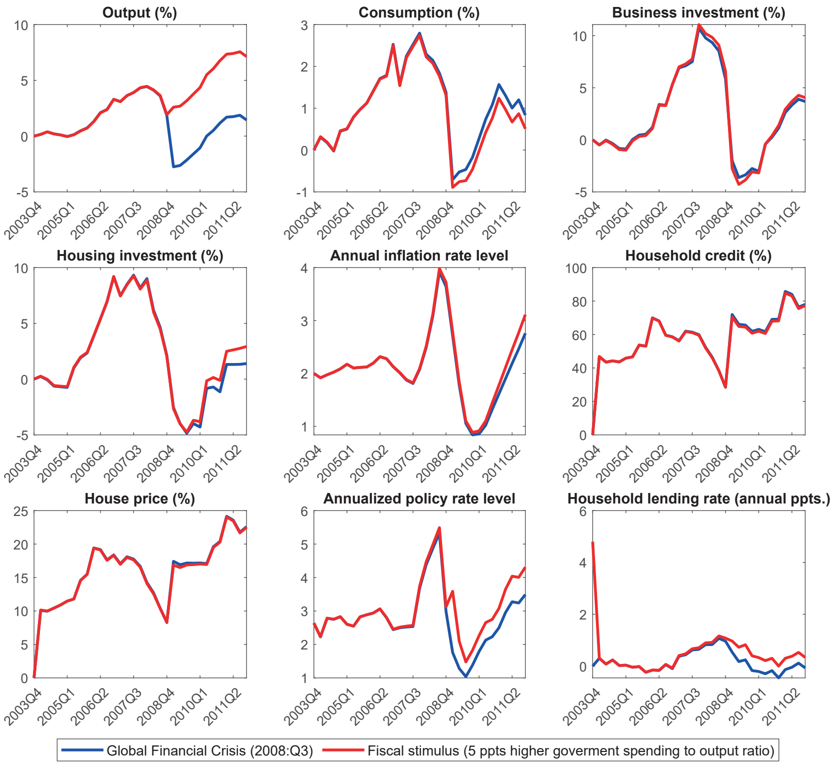


Figure 16. : Fiscal stimulus during the GFC



Appendix A: Estimation procedure

Data sources and descriptive statistics

Table A.1—: Dating of financial crises

country	Start of crisis	Country	Start of crisis
Australia	1989q4	Korea	1997q3
Austria	2007q4	Netherlands	2008q1
Belgium	2007q4	New Zealand	1987q4
Canada	1983q1	Norway	1988q3; 2008q3
Denmark	1987q1; 2008q1	Portugal	1983q1; 2008q4
Finland	1991q3	Spain	1978q1; 2009q1
France	1991q2; 2008q2	Sweden	1991q1; 2008q3
Germany	2001q1; 2007q3	Switzerland	1991q1; 2008q3
Greece	2010q2	United Kingdom	2007q1
Italy	1991q3; 2011q3	United States	1988q1; 2007q3
Japan	1992q1		

Notes: The table reports the periods at which the different countries in our sample experienced a financial crisis. The reported dates concern the start of the crisis and have been determined by relying on the financial crisis classifications suggested by Lo Duca et al. (2017) and (Laeven and Valencia, 2020, 2013), among others.

Table A.2—: Data sources

Variable	Source	Frequency	Note
Real GDP	OECD	Quarterly	
Credit	BIS	Quarterly	5-year growth in credit deflated by CPI
Inflation	OECD	Quarterly	Growth rate of CPI
House price to income	OECD	Quarterly	5-year growth in house price to income
Equity	OECD	Quarterly	5-year growth in equity price deflated

Notes: This table documents data sources for each relevant variable.

Table A.3—: Summary Statistics

Variable	N	Mean	Std. dev.	p25	p75
Real credit growth (5-years)	3,276	5.11	5.14	1.69	7.46
House price to income growth (5y)	2,828	.72	4.0	-1.93	3.07
Real return on equity (3y)	3,199	7.17	17.79	-3.87	13.73
Real interest rate (3y)	2,897	-0.24	0.93	-0.76	0.25

Notes: This table presents the summary statistics for each of the relevant financial variables.

Table A.4—: Finanical vulnerability measures and future large GDP shortfall

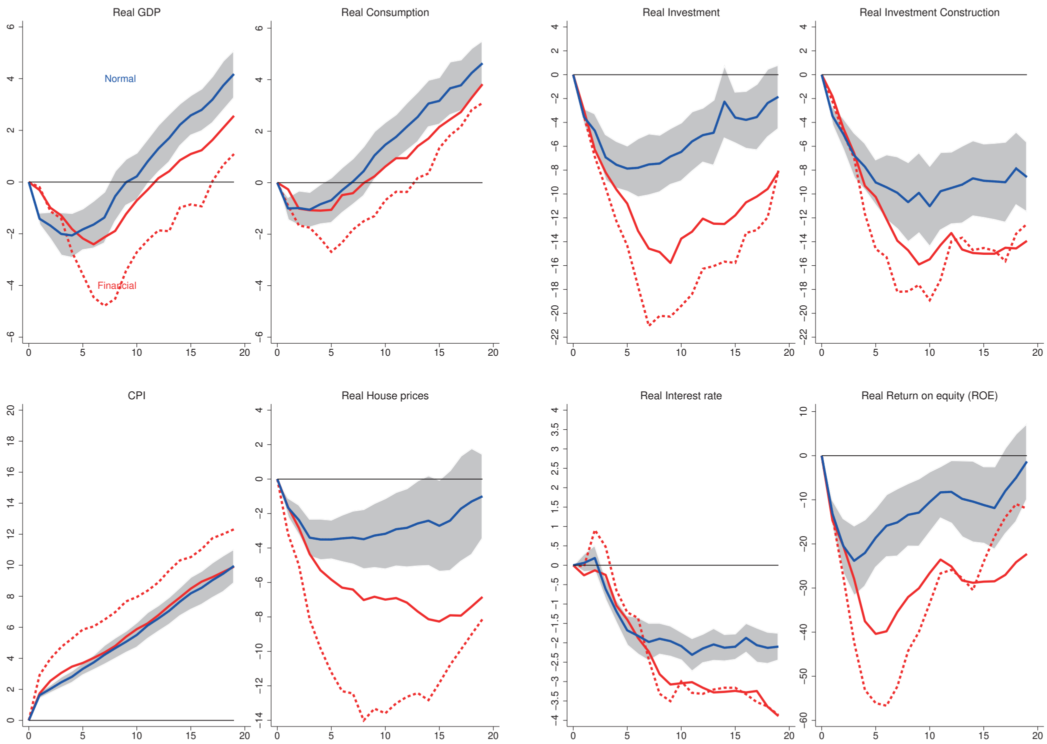
	No. of large GDP shortfall associated with	Average financial imbalances
Real credit (5Y av. growth) > μ_i	69% (33 of 48)	10.3
Real house prices (5Y av. growth) > μ_i	54% (26 of 48)	9.2
Real return on equity (3Y av. growth) > μ_i	62% (30 of 48)	19.9
Real interest rate (3Y change) > μ_i	71% (34 of 48)	1.2

Notes: This table presents summary statistics of the correlations between future large GDP shortfall within our dataset and vulnerability indicators that exceed the country average, μ_i. We use the lower percentiles of the average real GDP growth distribution over a three-year horizon ($\frac{y_{i,t+12}-y_{i,t}}{3\times y_{i,t}}$), explicitly representing the bottom 10% of observations.

Table A.5—: Summary statistics for macroeconomic variables for the euro area

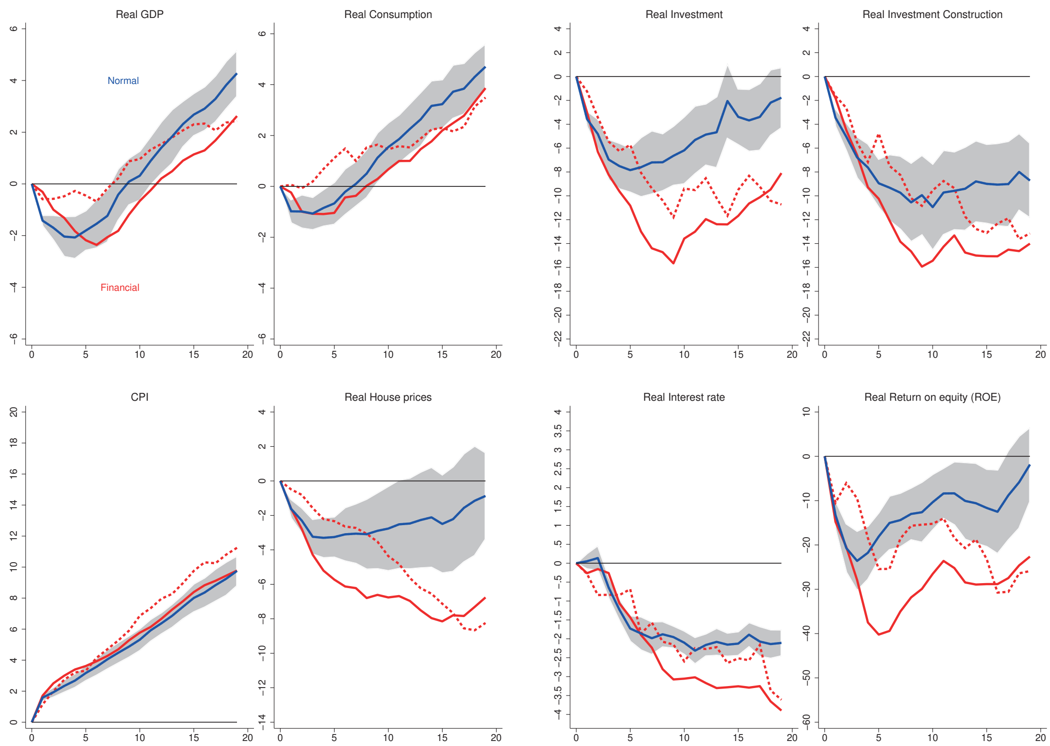
Average in the sample	**Normal times**	**Financial crisis**
Macroeconomic aggregates		
Consumption to GDP	0.50	0.52
Total investment to GDP	0.21	0.19
Housing investment to GDP	0.13	0.11
Financial variables		
Credit to non-financial corporations to GDP	1.36	1.59
Credit to households to GDP	0.58	0.63

Figure A.1. : Marginal impact following credit busts: normal recession and financial crisis



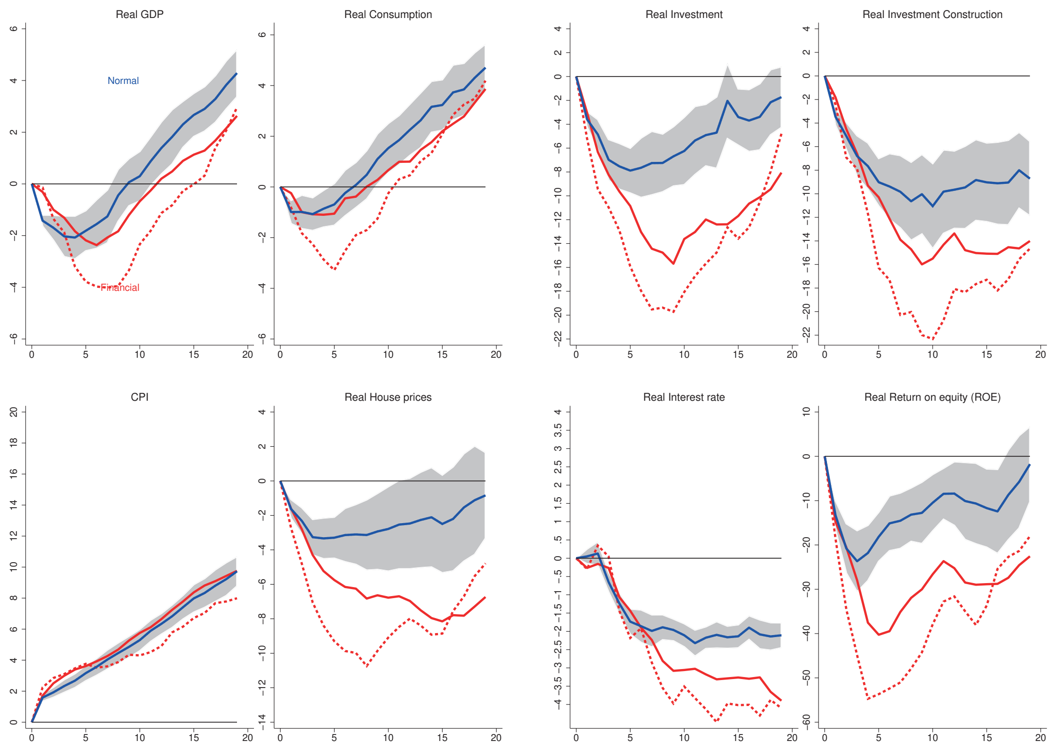
Notes: The figure plots the marginal impact on the macro and financial variables following a change in Credit. All variables are in log terms times 100 except for interest rates. The dashed blue line depicts the average effect of a normal recession with 95% confidence bands shown as grey areas. The solid red line reflects the effect of starting a financial crisis. The dashed red line represents the combined effect of starting a financial crisis and one standard deviation of excess credit growth (first row), house prices (second row), return on equity (third row) and real interest rate (fourth row).

Figure A.2. : Marginal impact following house prices correction: normal recession and financial crisis



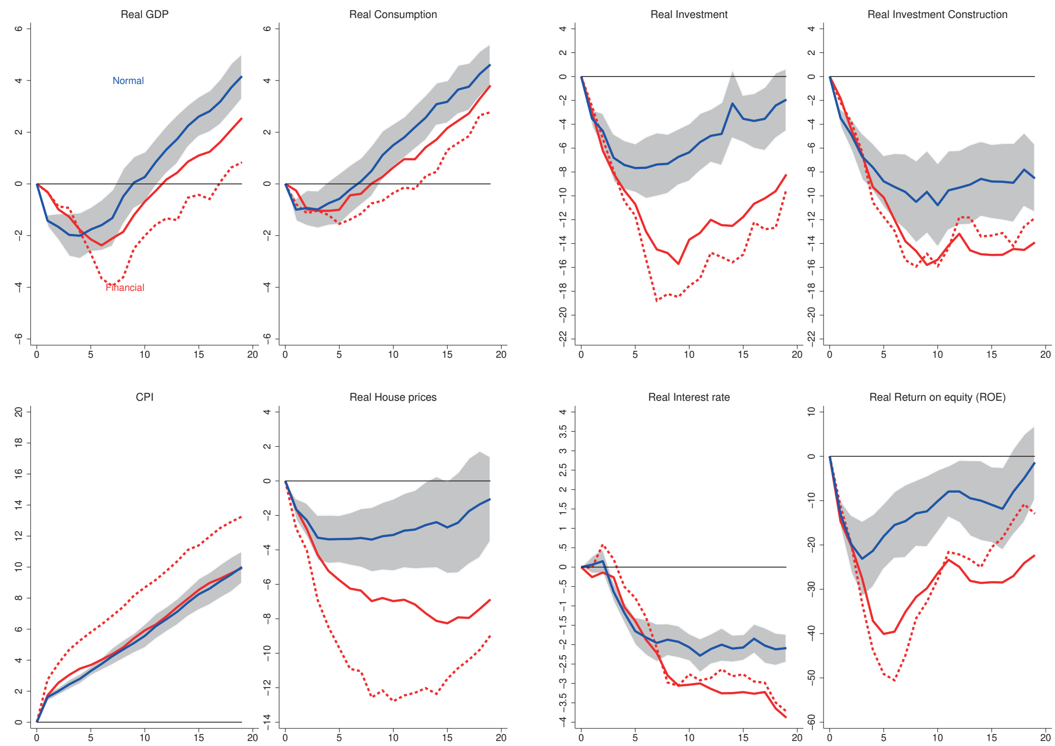
Notes: The figure plots the marginal impact on the macro and financial variables following a change in real house prices. All variables are in log terms times 100 except for interest rates. The dashed blue line depicts the average effect of a normal recession with 95% confidence bands shown as grey areas. The solid red line reflects the effect of starting a financial crisis. The dashed red line represents the combined effect of starting a financial crisis and one standard deviation of excess credit growth (first row), house prices (second row), return on equity (third row) and real interest rate (fourth row).

Figure A.3. : Marginal impact following ROE adjustments: normal recession and financial crisis



Notes: The figure plots the marginal impact on the macro and financial variables following a change in real return on equity. All variables are in log terms times 100 except for interest rates. The dashed blue line depicts the average effect of a normal recession with 95% confidence bands shown as grey areas. The solid red line reflects the effect of starting a financial crisis. The dashed red line represents the combined effect of starting a financial crisis and one standard deviation of excess credit growth (first row), house prices (second row), return on equity (third row) and real interest rate (fourth row).

Figure A.4. : Marginal impact following real interest rate adjustments: normal recession and financial crisis



Notes: The figure plots the marginal impact on the macro and financial variables following a change in real interest rate. All variables are in log terms times 100 except for interest rates. The dashed blue line depicts the average effect of a normal recession with 95% confidence bands shown as grey areas. The solid red line reflects the effect of starting a financial crisis. The dashed red line represents the combined effect of starting a financial crisis and one standard deviation of excess credit growth (first row), house prices (second row), return on equity (third row) and real interest rate (fourth rows).

Table A.1—: Response of Real GDP Growth. Excess Credit Experiment (=1sd): Normal vs. Financial crisis recessions

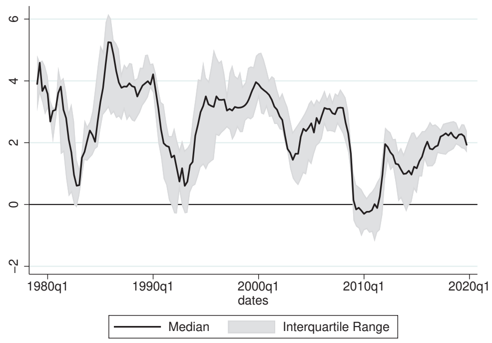
	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Quarter 5	Quarter 6	Quarter 7	Quarter 8	Quarter 9	Quarter 10
Normal recession (average)	-1.42***	-1.68***	-2.01***	-2.07***	-1.83***	-1.64***	-1.37**	-0.55	-0.01	0.22
	(0.12)	(0.27)	(0.43)	(0.44)	(0.41)	(0.47)	(0.51)	(0.50)	(0.46)	(0.47)
Financial recession (average)	-0.31	-0.99	-1.29	-1.82*	-2.18**	-2.41**	-2.14**	-1.89**	-1.24	-0.71
	(0.31)	(0.60)	(0.88)	(0.99)	(0.94)	(1.01)	(0.87)	(0.84)	(0.79)	(0.77)
Excess credit. Financial	0.06	-0.07	-0.06	-0.44	-0.70	-1.02*	-1.32**	-1.31***	-1.10**	-1.00**
	(0.23)	(0.49)	(0.71)	(0.78)	(0.70)	(0.54)	(0.49)	(0.46)	(0.47)	(0.43)
R^2	0.89	0.84	0.78	0.78	0.80	0.84	0.87	0.90	0.93	0.94
Normal = Financial (average). P-value	0.01	0.40	0.53	0.85	0.77	0.57	0.52	0.24	0.26	0.36
Normal = Financial (Excess Credit). P-value	0.81	0.89	0.93	0.58	0.33	0.07	0.01	0.01	0.03	0.03
Observations	89	88	87	87	87	86	85	85	85	85

	Quarter 11	Quarter 12	Quarter 13	Quarter 14	Quarter 15	Quarter 16	Quarter 17	Quarter 18	Quarter 19	Quarter 20
Normal recession (average)	0.79*	1.30**	1.70***	2.22***	2.58***	2.79***	3.19***	3.73***	4.18***	4.89***
	(0.45)	(0.47)	(0.48)	(0.42)	(0.40)	(0.42)	(0.46)	(0.49)	(0.47)	(0.43)
Financial recession (average)	-0.30	0.15	0.42	0.85	1.09	1.23	1.63	2.10	2.56**	3.11**
	(0.83)	(0.87)	(0.89)	(0.95)	(1.04)	(1.12)	(1.21)	(1.24)	(1.22)	(1.29)
Excess credit. Financial	-0.98**	-1.01**	-1.16**	-0.91**	-0.97**	-1.08**	-0.80	-0.72	-0.74	-0.52
	(0.44)	(0.41)	(0.42)	(0.40)	(0.40)	(0.42)	(0.47)	(0.56)	(0.73)	(0.79)
R^2	0.95	0.95	0.95	0.96	0.96	0.95	0.95	0.95	0.96	0.96
Normal = Financial (average). P-value	0.29	0.26	0.22	0.16	0.16	0.16	0.20	0.20	0.20	0.17
Normal = Financial (Excess Credit). P-value	0.04	0.02	0.01	0.03	0.02	0.02	0.10	0.21	0.33	0.52
Observations	85	85	85	85	84	84	84	84	83	82

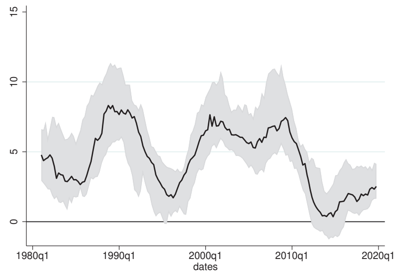
Notes: The table shows results with robust standard errors reported in parentheses. Statistical significance levels are denoted as follows: $***p < 0.01, **p < 0.05, *p < 0.1$. The findings correspond to local projections of growth in real GDP for quarters 1-20 of the recession/recovery period. Excess credit, followed by either "Normal" or "Financial," denotes the marginal effect of excess credit accumulation above the historical mean on the average path in Normal and Financial crisis recessions, respectively. In practice, when excess credit is one standard deviation above the mean, the path of real GDP growth in a financial crisis recession can be calculated as the sum of the Financial recession coefficient and the Excess Credit, where the Financial coefficient is multiplied by one. The "Normal = Financial" tests the null hypothesis that the coefficients for each type of recession are the same for the average and Excess Credit cases. The p-values of the tests are provided to show the statistical significance of the results.

Figure A.5. : Median and Interquartile range of the selected indicators across the sample of countries

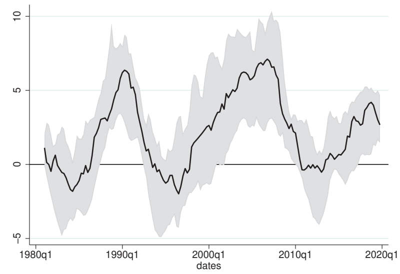
(a) Real GDP growth (average annual % over 3 years)



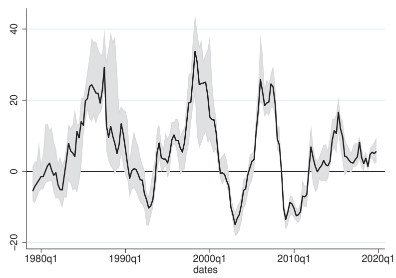
(b) Real Credit growth (average annual % over 5 years)



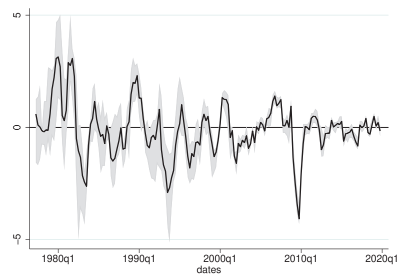
(c) Real house price growth (average annual % over 5 years)



(d) Real equity return (average annual % over 3 years)



(e) 1-year change in real interest rate



European Stability Mechanism

6a Circuit de la Foire Internationale
L-1347 Luxembourg

Tel: +352 260 292 0

www.esm.europa.eu

info@esm.europa.eu

Publications Office
of the European Union