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Enrico Minnella, Ana Pereira, Eugen Tereanu

The devil in the DeTail: assessing state-contingent tail effects of a releasable macroprudential capital buffer using a parsimonious agent-based framework

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Abstract

This paper develops an agent-based framework (DeTail) to assess the state-contingent tail effects of releasable macroprudential capital buffers. The model features heterogeneous firms, households, and banks, and a single central bank, all interacting in a fully integrated, stock-flow consistent framework which generates endogenous credit cycles. Using this approach, we evaluate how time-varying capital requirements affect the time-varying distributions of credit growth, firm and household default rates, and bank losses along the credit cycle. Policy experiments show that releasing capital buffers during economic downturns preserves credit supply by improving risky (lower-tail) credit outcomes, reduces both household and firm defaults, and supports macro-financial resilience by limiting tail bank losses. At the same time, capital buffer accumulation during upturns imposes minimal costs and does not significantly constrain lending. These findings support the active use of releasable buffers to mitigate systemic risk and smooth credit cycles without weakening the banking system.

JEL Classifications: C63, E44, E58, G28.

Keywords: Agent-based modelling; Macroprudential policy; Macro-financial linkages; Credit cycles; and State-dependent effects.

Non-technical summary

The COVID-19 pandemic highlighted the challenges of operating macroprudential capital buffers during periods of stress. Although buffers are designed to be drawn down in downturns to support lending, empirical evidence shows that banks were often reluctant to use them due to, inter alia, concerns about stigma and possibly adverse market reactions when capital ratios approach regulatory minima. These usability issues have since motivated a policy debate on whether a more active and systematic build-up and use of releasable buffers could better support lending and the overall resilience of the banking system under adverse conditions.

To contribute to this debate, the paper introduces the DeTail agent-based model (ABM) as a framework to assess the state-contingent tail effects (costs and benefits) of a releasable macroprudential capital buffer.[1] The model simulates macroprudential policies in a credit-driven granular economy with heterogeneous firms, households, and banks, and a central bank, all interacting in a fully integrated, stock-flow consistent framework. It significantly extends the endogenous credit cycle framework of Gross (2022) by incorporating a housing market with mortgage borrowing, lending by multiple banks subject to risk-based capital requirements, and a central bank to set macroprudential policies and manage interbank reserve transfers. These features enable a detailed analysis of the impact of releasable buffers on the time-varying distributions of credit growth, firm and household default rates, and bank losses (including the size and frequency of potential resolution authority interventions) along the credit cycle, with a focus on the evolution of risks and policy impact in the tails.

To assess the costs and benefits of a releasable buffer, we look at the tail impact of building and releasing a time-varying releasable capital buffer relative to a model with time-invariant capital requirements, during economic upturns as well as downturns. The endogenous credit cycle feature also allows us to evaluate the implications of a releasable buffer on the duration and amplitude of these cycles.

The tail analysis shows that releasing buffers during downturns helps to reduce the frequency of negative credit growth episodes and preserve credit supply, decrease the severity of firm and household defaults, and overall supports banking system resilience. At the same time, buffer accumulation during

[1] Tail effects refer to outcomes in the bottom 25% (first quartile) or top 25% (third quartile) of the distribution, depending on the variable under consideration and whether costs or benefits are being examined.

upturns does not materially constrain lending and may even improve credit quality by limiting excessively risky lending to the most highly leveraged firms. Furthermore, a releasable buffer also notably dampens the amplitude and duration of credit cycles, contributing to overall financial stability.

Overall, the findings support a more active use of releasable macroprudential buffers as a tool to mitigate the most severe credit outcomes, maintain the resilience of the banking sector and overall enhance financial stability. The DeTail model also illustrates the value of agent-based approaches for policy analysis by offering a granular and flexible simulation framework for evaluating macroprudential interventions in a distribution-focused, state-contingent setting.

1 Introduction

The importance of releasable macroprudential capital buffers in enhancing bank resilience and supporting credit provision during periods of stress was re-emphasised by the COVID-19 pandemic. While post-Global Financial Crisis reforms strengthened banking system resilience, the pandemic highlighted challenges of operating macroprudential capital buffers in a countercyclical manner. Although macroprudential buffers are designed to be drawn down in adverse conditions to avoid bank deleveraging and stabilise credit supply, empirical evidence showed that they were often underutilised by banks during downturns (see Couaillier et al., 2025; Mathur et al., 2023, among others). Banks' reluctance to draw down capital buffers during downturns is partly driven by concerns about stigma and the risk of adverse market reactions when capital ratios approach regulatory minima.[2] Additionally, the pandemic experience also showed the desirability of sufficient macroprudential space to moderate adverse shocks which can also occur irrespective of the phases of the financial cycle (Detken et al., 2025).

Consequently, much of the recent policy debate in Europe and the UK has focused on promoting the use of capital buffers. One direction is the active and systemic use of releasable buffers, including their use in response to a broader range of shocks.[3] Releasable macroprudential buffers, such as the Countercyclical Capital Buffer (CCyB), are designed to vary over the credit cycle. Their pro-active build-up and release can help to mitigate banks' concerns about drawing down capital to maintain lending during downturns. Consistent with this view, several countries, including EU member states as well as the UK, released the CCyB during the COVID-19 pandemic and other stress episodes to encourage buffer use and sustain lending. Although the conceptual rationale for such time-varying buffers is well established, evidence on their state-contingent effects, in particular regarding tail risks, remains limited. This paper contributes to this debate by analysing how releasable buffers impact the tails of distributions of key macro-financial and banking system outcomes along the cycle. We examine both

[2]Banks may be reluctant to draw down capital buffers during periods of stress due to concerns about market stigma. Using buffers may be interpreted by the market as a signal that a bank is under financial pressure or is weaker than its peers. This perception can lead to higher funding costs, reduced market access, or even credit rating downgrades (see Basel Committee on Banking Supervision, 2022; European Central Bank, 2022). As a result, banks may prefer to maintain buffers during periods of stress, even when the regulatory framework allows their use to absorb losses and support lending during downturns (for a separate discussion of challenges related to using bank capital to meet parallel regulatory requirements, see European Central Bank - European Systemic Risk Board, 2026).

[3]The capital buffer framework includes multiple buffers, which can be grouped into two categories: releasable and non-releasable. Releasable buffers are those that macroprudential authorities can reduce or release when risks materialise to prevent credit supply constraints during downturns. These buffers vary over the financial cycle and include the Countercyclical Capital Buffer (CCyB) and, in some cases, certain forms of the Sectoral Systemic Risk Buffer (sSyRB).

tail benefits of releasing the buffers during downturns, as well as the potential costs of their build-up during upturns.

For our analysis, we develop DeTail, a parsimonious, credit-driven agent-based model (ABM) which can generate complete distributions of our policy variables of interest (and in particular their tails).[4] The model builds on the framework in Gross (2022), where endogenous cycles arise from a combination of interest-bearing debt and downward nominal wage rigidity. To allow for the evaluation of macroprudential policies, we extend this framework by introducing a housing market with mortgage-financed homeownership, multiple heterogeneous banks subject to risk-based capital requirements, and a central bank that settles interbank reserve transfers and sets macroprudential policy. Together, these extensions allow the model to capture richer credit dynamics and the channels through which capital-based macroprudential policy affects firms, households, and banks simultaneously.

All agents' balance sheets are fully integrated and consistent as the cross-agent flows of funds result in corresponding changes in assets and liabilities across sectors (firms, households, banks, and central bank). The four types of agents engage in production/consumption, employment, borrowing/lending and dividend payment relations. Firms and households can default on their debt, leading to firm closures, job losses and collateral repossession, which in turn have macroeconomic implications. Since our economy is credit-driven, we assume that banks falling below their capital requirements are resolved in an orderly manner, i.e. without macroeconomic feedback effects.[5]

The DeTail framework contributes to the growing family of macro-financial agent-based models used to study financial stability and regulatory policies. Building on Gross (2022), it adds features aligned with recent macro-ABM applications analysing capital and borrower-based policies, such as Bardoscia et al. (2025), while maintaining a parsimonious structure suited for tail-focused, state-contingent policy analysis. The model also complements general-equilibrium approaches, such as the DSGE framework with three layers of default (3D) of Clerc et al. (2015), by assessing capital-based tools beyond average effects and without relying on linearisation. Finally, it connects to the recent literature emphasising non-linear and state-dependent effects of capital requirements (e.g. Lang and Menno, 2025), providing a macro-financial environment that captures heterogeneity, non-linear interactions,

[4]See Borsos et al. (2025) for a recent review of the application of ABM models in central bank policy analysis.

[5]This assumption is consistent with modern bank resolution frameworks, which aim to manage bank failures without destabilising the economy or burdening taxpayers. In line with these objectives, other ABM applications make a similar simplification (e.g. Bardoscia et al., 2025, assumes bank resolution is orderly and imposes no costs on the public).

and the full distribution of outcomes.

Using DeTail, we compare the macroprudential policy effects from a model with time-varying capital requirements (TVP) with simulations from a model with only time-invariant capital requirements (TIP). We focus on relative changes in the time-varying distributions of credit growth, default rates by borrower segments, and bank losses, evaluated separately over economic upturns and downturns. Specifically, we analyse policy-induced changes in the relevant (high risk) tail of these distributions, as well as changes in their volatility (the interquartile range) and shifts in the probability of extreme tail events.[6] As part of the policy benefit analysis, we additionally track the frequency and size of central bank interventions required to resolve ex-post undercapitalised banks. Finally, taking advantage of the endogenous cycles in our model, we also evaluate the impact of a releasable buffer on the amplitude and duration of the cyclical credit expansions and contractions using the approach in Drehmann et al. (2012).

Our key results confirm the importance of having sufficient releasable buffers in place. Firstly, we find that a releasable buffer can provide meaningful resilience benefits during downturns, by helping to reduce the occurrence of negative credit growth events and preserve credit supply when the economy is under stress. The release of the buffer in a downturn improves the lower (riskier) tail of real credit growth, reduces its volatility, and attenuates severe default events, especially for households, relative to a time-invariant capital regime. These improvements translate into reducing upper-tail (higher) bank losses as well as fewer systemic-level recapitalisation needs. Secondly, the macro-financial costs of building buffers during upturns are limited. Increasing the buffer does not materially tighten credit supply or raises default rates, reflecting the gradual implementation of higher requirements, which helps smooth adjustment costs. At the same time, the resulting slightly tighter credit supply conditions help to restrain credit to more highly leveraged firms, thereby improving credit quality and reducing default risks. Thirdly, the releasable buffer helps to shorten contractions and, to a lesser extent, limit the credit boom, resulting in a lower median cycle duration. The cycle amplitude also decreases, albeit modestly, in the presence of a releasable buffer.

[6] Policy-relevant tails are defined as the bottom and top quartiles of the distribution (the 25th or 75th percentile), depending on whether lower or higher values correspond to worse outcomes (costs) or better outcomes (benefits). Extreme tail events refer to percentiles lying beyond the policy-relevant tails, that is below the 25th percentile or above the 75th percentile.

The remainder of the paper is organised as follows. Section 2 reviews the related literature. Section 3 introduces the DeTail model used in the policy experiments. Section 4 presents the model's economic and empirical validation exercise supporting its use for policy evaluation. Section 5 discusses the policy evaluation strategy and results. Section 6 concludes.

2 Related literature

ABMs have gained traction in macroeconomic and macro-financial policy analysis because of their flexibility to address policy design and evaluation questions where "heterogeneity, complexity, non-linearity, emergence, heuristics and detailed rules" matter (Haldane and Turrell, 2018). A comprehensive survey of 60 years of ABM usage in economics and finance notes their significant complementarity to conventional economic modelling, particularly due to increased need to model heterogeneous agents with possibly differentiated (boundedly rational) behaviour whose non-linear interactions generate the aggregate (not necessarily equilibrium) outcomes (Axtell and Farmer, 2025). Within the general class of ABMs, macro-ABMs have been developed to study the economy as a complex, emerging system where both the aggregate but also granular effect of macroeconomic and macro-financial stabilisation policies can be evaluated (Axtell and Farmer, 2025; Dosi and Roventini, 2025). Recent developments also include macro-ABMs which generate micro-founded macro behaviour while also delivering a short-term forecast performance comparable to VARs and DSGE models (Poledna et al., 2023).

Reflecting this progress, ABMs have been increasingly used to analyse policies relevant to central bank mandates. A targeted survey of ABM modelling at central banks (Borsos et al., 2025) documents a wide range of applications ranging from systemic risk assessment and financial stability policies to monetary policy, payment systems and Central Bank Digital Currencies (CBDCs) and the analysis of climate risks. Following the global financial crisis, ABMs have been used to look into various regulatory policies (Krug and Wohltmann, 2016; Popoyan et al., 2020; Catullo et al., 2021), in particular the relevance of capital requirements to support the resilience of the banking system (Raberto et al., 2017; Van der Hoog and Dawid, 2019; Alexandre and Lima, 2020; Riccetti et al., 2022). Housing markets and related financial stability policies such as borrower-based measures have been included in a growing number of applications. Early contributions include the seminal works of Geanakoplos et al. (2012) and Axtell et al. (2014), while more recent policy-oriented analysis are provided by Cokayne (2019), Laliotis et al. (2020), Tarne et al. (2022), Mérő et al. (2023), Carro (2023), and Catapano (2023). More recently, Bardoscia et al. (2025) combine the granular housing market of Carro et al. (2022) with a complex macro-ABM of Popoyan et al. (2017), which features, inter alia, a labour market, multiple banks, a central bank, and a government, to explore the interaction of capital and borrower-based macroprudential policies in the UK.

Against this background, our DeTail agent-based framework lies within the family of macro-financial ABMs and is closely related to the growing strand of applications analysing financial stability and regulatory policies. From a macroeconomic perspective, it builds on the stock-flow consistent macro-ABM approach of Gross (2022), who proposes a parsimonious model in which endogenous economic cycles emerge from interest-bearing debt and downward nominal wage rigidity. Two of the stylised facts generated in the model are particularly relevant for macroprudential policy analysis: a) procyclical leverage and b) default cascades arising at the peak of the cycle.

We expand this modelling framework along three important dimensions. First, we introduce a housing market and mortgage borrowers, thereby incorporating the two core borrowing sectors of the economy. Second, we allow for multiple banks that supply credit to both firms and households and that are subject to risk-based capital requirements set by a central bank. Third, we add a central bank to manage interbank reserve transfers and set macroprudential policies, which are not present in the original framework. Importantly, firms and households can default on their loan obligations, with defaults affecting banks' capital ratios. When banks become undercapitalised, they are resolved without economic consequences.

Combining endogenous cycles with heterogeneous borrowers and multiple banks provides a unique framework for analysing capital-based policies. Specifically, we can assess the state-contingent impact of releasable capital buffers on specific tails of the distribution of variables of interest such as credit growth and agent defaults. The cyclical nature of the DeTail framework further allows an evaluation of the effects of the policy on the amplitude and duration of economic expansions and contractions. Finally, even though bank defaults do not generate direct macroeconomic losses in the model, we can still explore some indirect effects through the simulated cost of bailouts and the proportion of bank assets under default.

In this sense, our model closely relates to Bardoscia et al. (2025), as both frameworks analyse the interaction between housing markets, banks, and macroprudential capital-based policies within a macro-ABM setting. However, our approach is considerably more parsimonious and, through its endogenously generated cycles is specifically well-suited for a state-contingent and tail-focused assessment of macroprudential capital policy rules which is, to the best of our knowledge, novel in the literature. The smaller parameter space may prove valuable in future attempts to calibrate our framework for a comparable assessment across countries.

The DeTail model also relates to and complements existing general-equilibrium and banking sector models used in macroprudential policy analysis. General equilibrium models based on the DSGE model with three layers of default by Clerc et al. (2015) have been widely used to evaluate the risk-based selection of various macroprudential instruments (Azzone and Pirovano, 2024) as well as compute the risk-based calibration of a positive neutral countercyclical capital buffer (Herrera et al., 2025). This micro-founded DSGE model with financial frictions includes representative borrowing firms and households and two types of representative banks, specialising respectively in firm and household lending. The model is solved through standard linearisation around a steady state (equilibrium). Firms, households and banks maximise utility, profits and the NPV of equity. Importantly, borrowers can default on their loans which may lead to bank default when the loan return, subject to an idiosyncratic shock, falls below the cost of deposits. The higher the bank risks and leverage (the lower the capitalisation), the higher the probability that banks default. The DeTail framework complements this model by allowing an assessment of macroprudential capital policies not only in expectation, but also in terms of their state-contingent and tail-focused effects, which are features difficult to capture in representative-agent or linearised DSGE settings. Moreover, by modelling each sector as a time-varying distribution of (interacting) firms, households and banks, each with pre-specified behavioural rules, it offers an alternative to the fully optimising representative agent paradigm.

Recently, Lang and Menno (2025) use a non-linear structural banking sector model to show that the effects of changes in capital requirements on bank lending are strongly state dependent. Their work discusses both the "pricing" channel (lending rate) and the "quantity" channel (loan supply) and relates the strength of these channels to banks' capital positions and profitability. Importantly, they highlight the need for a non-linear modelling approach to determine a state-differentiated effect of macroprudential policies. The DeTail model complements this analysis by providing a macro-financial agent-based perspective that embeds similar concerns about non-linearity and state-contingent effects while allowing for a granular and tail-focused assessment of policy impacts.

Finally, our model contributes to a growing strand of work that assesses the distributional effects of macroprudential policies by explicitly modelling agent heterogeneity. This has become an increasing focus for several central banks. For example, Bush et al. (2025) highlight the importance of incorporating heterogeneity into analytical frameworks as a key step towards improving the evaluation of macroprudential policies.

3 DeTail model

This section introduces the DeTail model - an agent-based macro-financial framework used to assess the tail effects of releasable capital buffers over the credit cycle. It is organised as follows: subsection 3.1 provides a high-level description of the model and sets out the sequence of interactions between agents; subsections 3.2, 3.3 and 3.4 discuss the behaviour of firms, households and banks, respectively; and subsection 3.5 discusses the role of the central bank within the model and the capital requirements framework.

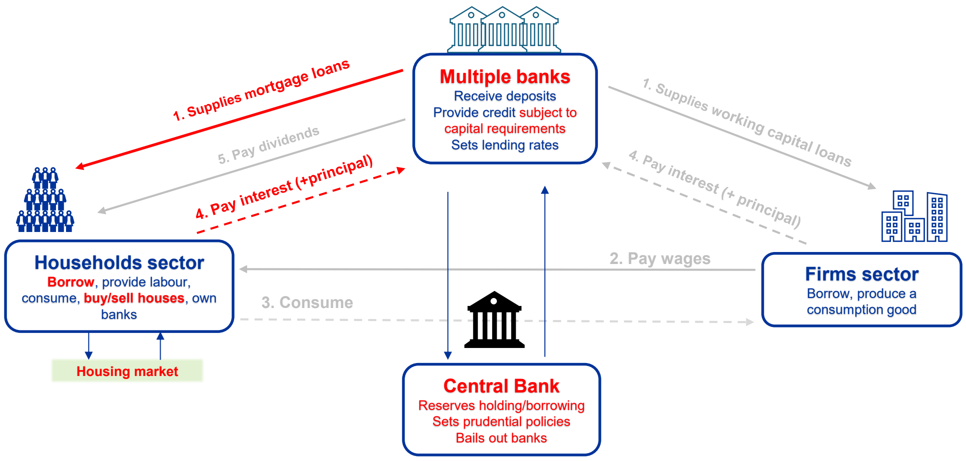
3.1 Model overview

The DeTail model is a parsimonious stock-flow consistent agent-based model. It relies on four types of agents - heterogeneous firms, households, banks and a single central bank – that interact in three economic sectors, as illustrated in Figure 1.[7] Agents engage in production/consumption, employment, borrowing/lending and dividend payment relations. The macroeconomy emerging from the agents' interaction is primarily credit-driven. The balance sheets are fully integrated and consistent across agents, as the cross-sector flows of funds result in corresponding changes in agent balance sheets. As discussed in section 2, we extend the Gross (2022) model in three key dimensions, highlighted in red in Figure 1. Firms and households can default, but in our current specification, any bank that breaches its capital requirements is recapitalised by the central bank, so that bank failures do not result in credit

[7] Heterogeneity across agents is multidimensional in our model. For example, firms are heterogeneous in terms of balance sheet size but also behaviour (e.g. active vs inactive (defaulted) firms).

supply contractions on the wider economy.[8] This simplification reflects an assumption of an orderly resolution and allows us to focus on the state-contingent costs and benefits of a releasable capital buffer rather than modelling systemic contagion from bank failures.

Figure 1: DeTail model



Note: The figure illustrates the structure of the DeTail model, which is built on the framework developed in Gross (2022). Elements highlighted in red indicate the extensions introduced in the DeTail model.

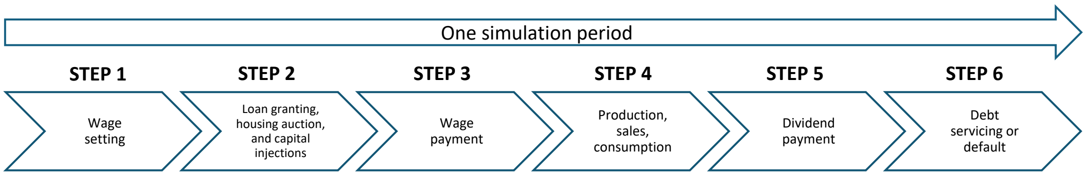
At the start of each period, firms compute their labour costs (wage bill) based on firm-specific wages set for that period. They then assess their financing needs, and when necessary, apply for loans to meet wage payments. Simultaneously, a subset of households participates in the housing market auction to gain home ownership while the remaining households are assumed to reside in social housing. Successful household bidders apply for mortgage loans to finance their purchases. The simulated economy emerges from six iterative steps each period, driven by agents' interactions. Figure 2 summarises the sequence of these events.

Banks extend credit only if their capital ratio exceeds capital requirements, not exceeding capital requirements might result in credit rationing. Firms that are denied credit become inactive and cease production for some time, rendering their assigned workers unemployed. Households unable to secure mortgage loans remain in social housing and may re-enter the auction in later periods. Because the model is credit-driven, each bank is required to satisfy a minimum share of the loan demand it receives,

[8]In its current specification, DeTail can be considered as a 2D+ type of model rather than a 3D model as in Clerc et al. (2015). Firms and household loan default result in losses to banks that can affect their capital ratios. Given that our economy is fundamentally credit driven, capital ratios below capital requirements are compensated by central bank capital injection to support credit supply, akin to orderly bank resolution. Various forms of orderly bank resolutions are common in the macro-ABM literature (e.g. Popoyan et al., 2017; Bardoscia et al., 2025) and modelling the macroeconomic feedback from bank default is left for future research.

defined as a fixed percentage of the wage bill of its client firms. When a bank's capital ratio is insufficient to satisfy this minimum while remaining compliant with capital requirements, the central bank injects capital into the bank to restore its lending capacity.

Figure 2: Sequence of events in each period



Note: The sequence of events largely follows the structure of the original model with differences in step 2, which incorporates the housing market and capital injections, and in step 6, which includes mortgage debt servicing and household default.

Next, active firms pay wages to their employees and produce the consumption good. Households then allocate a fraction of their available resources to consumption, selecting a supplying firm at random. This assumption introduces idiosyncratic demand shocks at the firm level, which are the sole source of endogenous cycle fluctuations in the model. Prices are firm-specific and determined by demand, under the assumption that all output is sold within the period, with no inventory carried over. Subsequently, each bank that did not receive a capital injection distributes dividends, provided its capital ratio exceeds the target threshold for dividend payments. These dividends are allocated equally across households, thereby increasing their disposable income for consumption in the subsequent period. After production and consumption, firms and households service their debt obligations. Indebted firms, including inactive ones, use their available resources to repay outstanding loans. Firms either: (i) repay the debt in full when resources exceed the debt amount; (ii) roll over the outstanding debt to the next period when resources are sufficient to cover only interest payments; or (iii) default when they cannot cover at least interest payments. In the case of default, the firm is shut down for two periods, and the bank seizes its deposits to mitigate losses. Indebted households face similar decisions when making mortgage payments. They either make the full annuity payment, pay only interest and roll over the outstanding principal, or default, in which case the bank repossesses the house pledged as collateral. Unlike defaulting firms which cannot access the credit market for two periods, defaulting households may re-enter the mortgage market already from the next period.

Tables 1 and 2 display the balance sheets for the four agent types and the corresponding flow of funds between agents in each period, respectively. This integrated view highlights how every outflow from one sector corresponds to an inflow to another, ensuring consistency in balance sheet updates across agents.

Table 1: Agents' integrated balance sheets

Assets/Agents	**Firm (f)**	**Household (h)**	**Bank (b)**	**Central Bank (cb)**	Σ
Loans	$-L_{f,b}$	$-L_{h,b}$	$L_b = \sum_f L_{f,b} + \sum_h L_{h,b}$		0
Deposits	$M_{f,b}$	$M_{h,b}$	$-M_b = -(\sum_f M_{f,b} + \sum_h M_{h,b})$		0
Reserve holdings			R_b	$-R_{cb} = -\sum_b R_b$	0
Reserve issuance			$-B_b$	$B_{cb} = \sum_b B_b$	0
Net worth	NW_f	NW_h	NW_b	NW_{cb}	0

Table 2: Agents' flow of funds

Flows/Agents	**Firm (f)**	**Household (h)**	**Bank (b)**	**Central Bank (cb)**	Σ
Wages	$-\sum(w_{f,t} \times n)$	$+\sum(w_{f,t} \times n)$			0
Consumption	$+\sum(p_{f,t} \times Y_{f,t})$	$-\sum(p_{f,t} \times Y_{f,t})$			0
Dividends		$+\sum div_{b,t}$	$-\sum div_{b,t}$		0
Interest on loans	$-\sum(i_t^F \times L_{f,t})$	$-\sum(i_t^H \times L_{h,t})$	$+\sum(i_t^F \times L_{f,t}) + \sum(i_t^H \times L_{h,t})$		0
Capital injections			$+\sum CI_{b,t}$	$-\sum CI_{b,t}$	0

Notes: The table only shows interactions between agents that result in changes in net worth.

3.2 Firm behaviour

Firm behaviour in the model is determined by wage and price setting rules, production and borrowing decisions, and debt obligations. Our simulated economy is populated by a total of F heterogeneous firms, indexed by f, that produce a homogeneous consumption good using household labour as their only input. Each firm holds deposits and possibly an outstanding loan on its balance sheet. Let $M_{f,t}$ denote firm f's deposits at time t, and $L_{f,t}$ its outstanding loans at time t.

Wages in the simulated economy are firm-specific and incorporate nominal rigidity. Each firm employs a fixed number of households as workers, given by $n = \frac{H}{F}$, where H is the total number of households in the model, with $H > F$. This workforce per firm remains constant over the simulation. Each active firm pays a firm-specific nominal wage, denoted by $w_{f,t}$. Firms that become inactive (due to default or credit denial) cease operations and therefore do not set wages while inactive. Wages are downwardly rigid, as documented in the empirical literature summarised in Gross (2022), such that firms only increase wages when past inflation exceeds past wage growth; otherwise, wages remain unchanged. For an existing firm

$$w_{f,t} = w_{f,t-1} \times e^{\Delta w_{f,t}}$$

where $e^{\Delta w_{f,t}}$ is a wage growth factor. New entrant firms, which have no wage history, set

$$w_{f,t} = \bar{w}_{t-1} \times e^{\Delta w_{f,t}}$$

where $\bar{w}_{t-1}$ is the economy-wide average wage in period $t-1$. A new firm, lacking its own wage history, benchmarks its initial wage on last period's average wage in the economy.

Wage growth, $\Delta w_{f,t}$, is determined by comparing the firm's price inflation in period $t-1$ with its wage growth in the same period and applying an inflation pass-through parameter, $\kappa \in (0, 1]$.[9] Formally,

$$\Delta w_{f,t} = \begin{cases} \kappa \times \Delta p_{f,t-1}, & \text{if } \Delta p_{f,t-1} > \Delta w_{f,t-1} \\ 0, & \text{if } \Delta p_{f,t-1} \leq \Delta w_{f,t-1} \end{cases}$$

For existing firms, $\Delta p_{f,t-1}$ denotes a firm's own price inflation in period $t-1$, and $\Delta w_{f,t-1}$ is its wage growth in period $t-1$. For a new entrant, inflation and wage growth are taken from the aggregate economy, $\Delta p_{f,t-1} = \Delta \bar{p}_{t-1}$ and $\Delta w_{f,t-1} = \Delta \bar{w}_{t-1}$. This rule ensures nominal wage rigidity: wages do not fall, and increases occur only when price inflation outpaces past wage growth, and even then, only partially, depending on κ.

All firms start with the same initial nominal wage, which is arbitrary and has no effect on results, as only relative wage changes matter in the model. The total wage bill for firm f at time t is given by: $WB_{f,t} = w_{f,t} \times n$.

[9] We allow $\kappa < 1$ to capture incomplete wage indexation. Partial pass-through dampens "second-round" wage–price feedback, where strong indexation can amplify inflationary shocks through mutually reinforcing wage and price adjustments, limiting inflation persistence.

Firms borrow only when their resources are insufficient to meet the wage payments. In each period t, if a firm's deposits do not cover its wage bill, it demands a working-capital loan of size $l_{f,t}$. This loan amount equals the difference between the wage bill and the firm's deposit balance.[10] Firms do not necessarily borrow every period; however, in the first simulation period all firms start with zero deposits ($M_{f,0} = 0$) and therefore must borrow to pay wages. The interest rate on these loans, i_t^F, varies over time and is set by the bank based on the economy-wide average credit risk of firm loans (see subsection 3.4 for details). This is consistent with the model's assumption of no bank competition, and does not constrain the model, as firms operate in a common sector and can reasonably be assumed to sustain stable banking relationships over time. Each new loan has a maturity of one simulation period ($d_{f,t} = 1$).[11]

Bank credit supply is not perfectly elastic, as banks must satisfy regulatory capital requirements, leading to credit rationing. Consequently, not all firms obtain the credit needed to meet their wage-bill obligations. Firms that fail to secure credit become inactive for two consecutive periods, generating unemployment. Some of these firms may still hold outstanding debt; however, temporary inactivity due to credit denial does not automatically trigger default. As long as a firm has sufficient deposits to cover its interest payments, it remains solvent, despite ceasing operations (see default conditions below).

Firm output is linear in labour, with each worker producing one unit of the consumption good per period. In each period t, each active firm f produces $Y_{f,t} = n$, implying that labour productivity is fixed and normalised to one unit of output per worker. Because firm-level output is proportional to its number of employees, the aggregate output in period t equals the sum of output across all firms. The assumption of constant returns to labour ensures that scaling the number of firms or workers expands aggregate output proportionally.

Firms set prices to fully clear their output each period, ensuring that nominal demand equals revenue and that no inventory is carried forward. In this single-good economy, firms produce a homogeneous consumption good but set their own prices based on the demand they face from households, who choose a supplier each period (see subsection 3.3). Given these demand conditions, firms select a

[10]When the bank extends this loan, it simultaneously credits the firm's deposit account with the same amount, thereby creating new money in the economy.

[11]This is interpreted as one month in the model by calibrating the annual interest rate consistent with 12 model periods.

price that guarantees the sale of their entire output. Formally, the pricing rule is:

$$p_{f,t} = \frac{\sum_{h \to f} c_{h,t}}{Y_{f,t}}$$

where $\sum_{h \to f} c_{h,t}$ is the nominal consumption allocated by households to firm f in period t. This rule ensures market clearing for firm f's goods market by equating revenue to nominal demand. It is also consistent with profit maximisation: setting a lower price would reduce profits by selling output too cheaply, while a higher price would leave some output unsold. As a result, the firm optimally clears its market each period. The aggregate price index is calculated by applying a price growth factor to the previous period index value. The growth factor is calculated as the ratio of the cross-sectional mean of firm-level prices in period t to that in period $t-1$. This approach ensures that the price index reflects the average proportional change in prices across firms over time.

Firms operate under limited liability, under which firms default when their deposits are insufficient to meet interest obligations. Default generates losses for the bank, which are partially mitigated through the seizure of the firm's deposits as recovery value. A defaulting firm becomes inactive for two periods, during which its workers become unemployed, and subsequently re-enters the market as a new firm with zero net worth and the same workforce. Conditional on avoiding default, the firm either repays the full principal and interest or, if only the interest can be paid, rolls over the outstanding principal to the next period. When rollover occurs, the new credit granted to the firm is added to its existing liabilities. Overall, in each period, some firms remain active and contribute to aggregate output, while others are inactive and contribute to unemployment. Importantly, inactivity can arise both from default and from credit denial.

3.3 Household behaviour

Household behaviour in the model is governed by decisions on consumption, housing market participation, and the servicing of mortgage debt. The simulated economy contains H heterogeneous households indexed by h. These households consume goods produced by firms, earn labour income, regularly participate in the housing market (financing purchases through borrowing), and hold equity stakes in banks, from which they receive dividends. Each household holds a deposit account at a bank and, if indebted, services a mortgage issued by the same bank. A household's net worth is defined as the difference between its deposits in period t, $M_{h,t}$, and its outstanding mortgage, $L_{h,t}$.

Housing demand and mortgage borrowing are modelled through a constrained homeownership process in which households participate in a double-auction market for houses, as illustrated in Figure 3. Only a fixed fraction of households, H_{frac}, can own a house in the model because housing supply is limited. At the start of the simulation, available houses are randomly allocated to households, designating them as initial homeowners. The remaining households live in social housing, where no rent is charged. However, households have an intrinsic demand for housing services that can be satisfied only via mortgage-financed homeownership. Consequently, those without a house enter the housing market and participate in a double-auction mechanism to acquire a dwelling, provided they can afford it.[12] This, together with the introduction of mortgage lending, is one of the key extensions we introduce to the original framework.

Household bids in the housing market are constrained by affordability considerations. Each prospective buyer submits a bid price, $p^{bid}_{h,t}$, for the house, which is capped by what the household can afford under a debt service-to-income (DSTI) constraint. Households are assumed to finance the entire purchase with a mortgage (100% loan-to-value ratio assumption) of duration $d_{h,t}$ at interest rate i^H_t. Accordingly, the bid reflects the maximum house price consistent with keeping mortgage payments within a feasible share of wage income. The maximum amount of income the household allocates to mortgage payments in each period is $DSTI_h \times (1 - MPC) \times w_{h,t}$, where $w_{h,t}$ is wage income, MPC represents the economy-wide marginal propensity to consume (i.e., the share of income available for mortgage payments), and $DSTI_h$ captures household-specific borrowing limit preferences.[13] Different households have different DSTI tolerances, introducing heterogeneity in how much of their income they are willing to commit to debt service.[14] Given this maximum affordable payment, the implied maximum mortgage, and therefore the bid price is:

$$P^{bid}_{h,t} = [DSTI_h \times (1 - MPC) \times w_{h,t}] \times \frac{1 - (1 + i^H_t)^{-d_{h,t}}}{i^H_t}$$

where the very last term is the standard annuity present-value factor. This affordability constraint

[12]Only households that are employed and do not already own a property can take part in the house auction.

[13]In our model, households allocate their wage income according to a fixed marginal propensity to consume (MPC). We use a common MPC for all households (an economy-wide value), for simplicity.

[14]The borrowing limit for each household is determined by sampling from a truncated Beta distribution, with scale and shape parameters α and β, and truncation bounds L and U. Specifically, the distribution is truncated between a minimum DSTI ratio of 5% and a maximum of 55%. This approach reflects heterogeneity in household borrowing capacity and ensures values remain within realistic policy bounds.

prevents households from taking on mortgage obligations that exceed a prudent share of their income.

Sellers set ask prices by indexing them to recent market conditions, adjusting prices in line with movements in the median transaction price. Sellers include households that have repaid their mortgages and are offering their homes for sale, as well as banks liquidating foreclosed properties (see more on household default below). At the start of the simulation, each house is assigned an initial price drawn from a cross-sectional distribution, denoted by P_t^j with $j = 1, \ldots, (H_{frac} \times H)$, where $(H_{frac} \times H)$ is total housing supply. Thereafter, each seller updates the asking price of house j based on overall market conditions. Specifically, the ask price is indexed to the recent median transaction price, including transactions involving foreclosed properties. The ask price for house j at time t is given by:

$$P_t^j = P_{t-1}^j \times \left(1 + \frac{\tilde{P}_{t-1} - \tilde{P}_{t-2}}{\tilde{P}_{t-2}}\right)$$

where $\tilde{P}_{t-1}$ denotes the median price of all houses transacted in period $t-1$. Thus, sellers adjust ask prices in line with recent market-wide price movements: increases in the median transaction price lead to higher ask prices, while stable or declining medians prompt sellers to maintain or reduce prices.[15]

A housing transaction occurs when a matched buyer–seller pair agrees on a price and the buyer successfully obtains mortgage financing, which may not always be possible due to credit supply constraints. A prospective buyer is considered successful when their bid price meets or exceeds the seller's ask price. In the model, the transaction price is set equal to the buyer's bid; thus, buyers may pay above the seller's minimum acceptable price. Given the assumption of 100% loan-to-value financing, the transaction price also determines the new mortgage principal $l_{h,t}$, if the household is able to secure the loan.

The prices of houses sold are updated to reflect their transaction values, while unsold house prices are adjusted using the growth rate of the median transaction price. The overall house price growth in the simulated economy is then calculated based on the average price of both sold and unsold properties.

[15] At the start of the simulation, when no house transactions have yet occurred, house prices are updated using a growth rate based on the median price of all houses in the market, rather than only those that have been sold.

Figure 3: Housing market: double auction mechanism

Notes: Transaction price equals the bid price. The eligible seller with the highest ask price (closest to bid) is selected. Unmatched buyers remain in social housing; unmatched sellers re-list in later periods.

Mortgage credit in the model is constrained by bank capital regulation, which affects whether successful bidders in the housing market can complete their transactions. A successful house bidder may not be able to obtain the mortgage it needs, in that case the transaction does not occur, and the household remains in social housing. If the household secures a mortgage, the purchase is completed, and the new homeowner begins servicing the debt each period. The interest rate on new mortgage loans is set by the banks based on the economy-wide average credit risk of household mortgages (see subsection 3.4 for details). Mortgage loans are long-term, with an average maturity of 30 years, considerably longer than the one-period maturity of firm loans.[16]

Household income in the model is generated through wage earnings and dividend payments, evolving with employment status and bank profitability. Households receive wage income, $w_{h,t}$, from supplying labour to firms, and dividend income, $div_{h,t}$, from holding bank equity. Wages are paid each period unless a household becomes unemployed due to the temporary inactivity of its employing firm. In that case, wage income is suspended for two periods, after which the household resumes employment at the same firm and wage payments restart. When banks accumulate capital in excess of regulatory requirements, they distribute dividends to households (see subsection 3.4). Importantly, unemployed households do not earn wages during the inactivity spell but may continue to receive dividend income.

[16]Maturities are randomly drawn from a lognormal distribution with mean μ_H, and standard deviation σ_H.

Household consumption is determined by a simple rule linking available resources to spending. Household income flows, i.e. wages and dividends, are added to savings from the previous period to determine the resources available for consumption and debt payments. Each period, a household allocates its consumption $c_{h,t}$ to a randomly selected firm, generating firm-specific demand. This assumption introduces the only stochastic element in the model, and it is important for generating the endogenous macro-financial cycles in the absence of external shocks. Households follow a simple consumption rule: they spend a fixed fraction of their available resources each period.[17] The consumption rule is:

$$c_{h,t} = MPC \times (M_{h,t-1} + w_{h,t})$$

When a household sells its house, the resulting increase in its deposit balance represents a temporary positive wealth shock. Instead of applying the standard consumption rule to this unusually large inflow, the model imposes a consumption-smoothing rule (a "Ferrari fix") to avoid an unrealistically sharp rise in consumption (see Appendix A for details).

Mortgage defaults arise when households cannot meet minimum debt-service requirements, resulting in foreclosure of the property. After allocating resources to consumption, a household uses its remaining deposits together with any dividend payout to service its mortgage. As with firms, the household either repays a part of the principal and interest or, if it can only cover interest, rolls over the outstanding principal to the next period. However, if available resources are insufficient even to meet the interest payment, the household defaults. In this case, the bank forecloses on the property, whose value may have changed relative to the original purchase price, and the repossessed house is placed in the next period's housing auction. For simplicity, the model does not impose an additional discount on foreclosed properties beyond what is already captured by housing market dynamics; as a result, bank credit losses may be understated relative to a setting with distressed-asset price effects.

3.4 Bank behaviour

The banking system in the model performs the following core functions: supplying and allocating credit across borrowers, setting interest rates, and distributing dividends. We introduce a number of B heterogeneous banks, indexed by b, subject to capital requirements and two forms of capital injections,

[17] For this calculation, available resources include beginning-of-period deposits and wage income received during the period. Dividend payments, which are distributed at the end of the period, are saved entirely until the next period.

one to sustain minimum credit supply and one to prevent bank insolvency. A bank's asset side consists of loans to firms ($L^F_{b,t}$) and households ($L^H_{b,t}$), $L_{b,t} = L^F_{b,t} + L^H_{b,t}$, and reserves held at the central bank, $R_{b,t}$. Total assets are therefore given by $A_{b,t} = L_{b,t} + R_{b,t}$. On the liability side, bank b holds deposits from firms ($M^F_{b,t}$) and households ($M^H_{b,t}$), $M_{b,t} = M^F_{b,t} + M^H_{b,t}$, and may borrow from the central bank $B_{b,t}$. Net worth (equity) is defined as $NW_{b,t} = A_{b,t} - (M_{b,t} + B_{b,t})$. All banks start the simulation with zero net worth. Over time, heterogeneity across banks emerges endogenously, reflecting differences in loan portfolio composition (e.g., loan size, maturity structure, and default events). Compared to a single bank, introducing relatively simple but multiple banks allows a more granular assessment of the impact of releasable buffers, as the ex-post heterogeneous bank balance sheets can inform the distribution of interventions and costs of safeguarding the banking system under a TVP regime.[18]

Banks begin the simulation with an evenly distributed customer base, which remains fixed over time and shapes the flow of deposits and liquidity in the system. At the outset, households and firms are allocated evenly across banks, such that each bank serves $n^H = \frac{H}{B}$ households and $n^F = \frac{F}{B}$ firms. Customers do not switch banks during the simulation, giving each bank a stable depositor base that can eventually become borrowers too. However, this fixed allocation does not imply a closed system per bank. When a customer of one bank transacts with a customer of another bank, funds move between banks through the settlement of central bank reserves (see Appendix A for details). These reserve flows redistribute liquidity across the banking system without directly affecting any bank's net worth.

Banks' credit supply is bounded by regulatory capital requirements, which limit their ability to meet all loan demand from firms and households. The primary role of banks in the model is to provide loans, differentiated by purpose and maturity. Firm loans are unsecured short-term credit used to finance working capital needs. Household loans (mortgages) are long-term and secured by housing collateral. Importantly, banks cannot expand lending without bound; their credit supply is constrained by capital regulation.

The credit supply of bank b in period t, denoted $CS_{b,t}$, is limited by its capital headroom, defined as the difference between its capital ratio and the regulatory capital requirement, both expressed in terms of a bank's risk-weighted assets (RWA). Subsection 3.5 and Appendix A provide additional details

[18]The balance sheet heterogeneity is a first step towards a richer modelling of the banking sector, e.g. through bank competition or differentiated business models, which, together with the macroeconomic feedback of complete bank default, we leave for future research.

about the risk-based capital requirements framework. Specifically, let $CAR_{b,t} = \frac{NW_{b,t}}{RWA_{b,t}}$ be the bank's capital ratio and CAR_t^{req} the regulatory capital requirement. The bank's credit supply corresponds to the maximum increase in RWA it can take on without breaching the capital requirement:

$$CS_{b,t} = \max\left[0, \frac{NW_{b,t}}{CAR_t^{req}} - RWA_{b,t}\right]$$

This rule limits the aggregate supply of credit to firms and households. When available credit is insufficient to meet demand, some loan applications are rejected. As discussed in subsections 3.2 and 3.3, firms that cannot obtain working-capital financing become inactive, while households unable to secure a mortgage forgo the housing transaction.

Capital injections in the model serve two purposes: ensuring minimum credit supply to firms and preventing banks from breaching regulatory capital requirements following losses. Although banks may deny credit to comply with capital requirements, each bank in the model must satisfy a minimum share of the working-capital loan demand it receives, defined as a fixed percentage, σ, of the wage bill of its client firms. When a bank's available credit supply is insufficient to meet this minimum, it receives an equity injection from the central bank. Effectively, the central bank recapitalises the bank pre-emptively to avoid a contraction in credit (see Appendix A for details). Banks capable of supplying at least σ percent of their firms' wage bill receive no injection. This mechanism is not present in the original model because banks are not subject to regulatory capital requirements and can therefore continue operating with negative equity without restricting credit supply. In our model, by contrast, capital requirements constrain banks' lending capacity. If this constraint causes credit supply to be substantially lower than firms' demand for working-capital loans, many firms may be unable to finance production, resulting in a collapse of the economy. The minimum credit provision rule is therefore introduced to preclude such outcomes, which may arise as a consequence of imposing regulatory capital requirements.

The central bank also injects capital into banks, when losses from firm and household defaults reduce a bank's capital ratio below the regulatory capital requirements. This is because the model does not allow banks to fail or exit due to insolvency. This assumption of a public backstop reflects historical crisis interventions, where authorities recapitalised banks to prevent a systemic credit crunch, and is consistent with an effective resolution framework, an assumption also used in Bardoscia et al. (2025).[19]

Both types of capital injections carry no economic costs in the model because taxes and shareholder dilution are abstracted from. This simplifying assumption allows the analysis to focus on how alternative capital regimes affect credit dynamics and bank resilience without introducing second-round macroeconomic effects. One output of our simulation is the frequency and magnitude of capital injections to avert bank insolvency under different regulatory settings (see section 5), which we interpret as an inverse indicator of banking-system robustness.

Banks allocate credit using a risk-based rule that prioritises safer borrowers. In each period, banks manage risk conservatively by ranking loan applicants according to their assessed creditworthiness and approving loans in order of increasing risk. For firms, applicants are ranked by their leverage ratio at loan origination, with lower-leverage firms considered safer due to a larger equity buffer and a lower likelihood of default. For households, banks use the debt-service-to-income (DSTI) ratio at loan origination as the main risk indicator. Households with lower DSTI ratios are viewed as safer because they have greater income capacity to meet mortgage payments in case of a shock. This risk-based allocation framework ensures that scarce credit is directed toward borrowers with the highest expected repayment probability and aligns with empirical evidence that banks tighten lending standards in downturns. Finally, each bank allocates a fixed share, λ, of its credit supply to firm lending, with the remainder allocated to household loans.

Firms can have multiple loans at the same time. When this occurs, the model consolidates the old and new loans into a single obligation for repayment purposes (see Appendix A for details). This simplification preserves computational tractability without altering the economic mechanisms driving firm behaviour. By contrast, household mortgages are not consolidated because each household holds at most one mortgage at a time.

Loan maturities differ across borrower segment and loan pricing reflects a markup over funding costs and aggregate segment-level credit risk. As outlined in subsections 3.2 and 3.3, firm debt is essentially short term while mortgage loans span multiple periods. Interest rates on new loans to both firms and households are set at origination and remain unchanged over the entire duration of the loan. In

[19] While this mechanism prevents bank runs and maintains credit flow, it could introduce moral hazard (implicit subsidies). In our model, we take this mechanism as an exogenous safety net rather than a choice, to strictly compare scenarios with different capital requirement regimes in a controlled way.

the absence of price competition, all borrowers within a segment face the same interest rate in a given period, irrespective of which bank they use or its specific (idiosyncratic) risk. Loan pricing follows a markup rule over funding costs and expected credit losses:

$$i_t^j = \mu + i_t^M + \frac{PD_t^j \times LGD_t^j}{1 - PD_t^j}, \qquad j \in \{H, F\}.$$

where, μ bank profit margin, i_t^M is the deposit rate, and PD_t^j and LGD_t^j denote the bank's expected probability of default and loss given default in borrower segment j.[20] Under this pricing rule, loan rates increase with credit risk: a bank charges a higher loan rate if it expects a larger share of loans in its portfolio to default or if the expected losses in the event of default are larger. We assume that banks form their expectations of PDs and LGDs in an adaptive backward-looking manner. That is, rather than forecasting, banks use realized default rates and losses as proxies for current risk levels (see Appendix A for details).

Dividend distribution is governed by a simple rule linking payouts to banks' capital positions, ensuring that dividends are paid only when banks remain above their internal target capital ratios. Banks distribute dividends to households, their equity holders, only when certain conditions are met. Each bank has a target capital ratio for distributions, denoted CAR_t^{target}, which establishes the minimum level of capital the bank aims to maintain relative to its risk-weighted assets. This target is identical across banks but varies with the regulatory regime and is typically set at or above the regulatory requirement to ensure that payouts occur only when banks are sufficiently capitalised.

A bank distributes dividends at period t only if it did not receive a capital injection in that period; and its capital ratio before considering interest income, loan losses and dividend payments is above its target capital ratio. The first condition ensures that banks that were just bailed out do not immediately pay that money out to shareholders, consistent with dividend restrictions following government support. If both conditions hold, the bank distributes all capital in excess of its target. The dividend amount is:

$$div_{b,t} = \max\left[0, \left(CAR_{b,t} - CAR_t^{target}\right) RWA_{b,t}\right]$$

which reduces the bank's post-dividend capital ratio to exactly its target level. This rule effectively

[20]Deposit rates are set to zero throughout the simulation as in Gross (2022) baseline simulation. Also, in our simulations, all banks use the same pricing rule, with the markups and credit risk parameters identical across banks.

keeps capital ratio at the targeted minimum while returning surplus capital to shareholders (see Appendix A for details). Dividend payments are allocated equally across the bank's household depositors, increasing their deposit balances but not their current-period resources for consumption (see subsection 3.3).

Debt servicing follows an annuity structure, under which borrowers either repay principal and interest, roll over principal, or default depending on their available resources. At the end of each period, all firms and households with outstanding loans are required to make debt payments, which amount to an annuity payment that covers interest and principal and is based on the loan's terms (see Appendix A for details). If the borrower has sufficient deposits to pay the full annuity amount, the loan amortises normally (i.e. the principal amount outstanding decreases). If deposits cover only the interest component, the borrower pays interest and rolls over the principal to the next period (i.e. the principal amount outstanding stays constant into the next period). If the borrower cannot even pay the interest due, the loan goes into default.

Default events trigger different recovery mechanisms for firms and households, reflecting the distinct nature of their loans and timing of loss recognition. When a firm defaults, the bank first seizes the firm's deposits to offset losses. If a defaulting firm $\widetilde{f}$ has outstanding loan $L_{\widetilde{f},t}$ and deposits $M_{\widetilde{f},t}$, the bank recovers:

$$seize_{b,\widetilde{f},t} = \min\left(M_{\widetilde{f},t}, L_{\widetilde{f},t}\right),$$

with any remaining loan value written off immediately. The model does not include non-performing loans or provisioning; losses are realized immediately and written off against capital. Household default follows a different process. When a household $\widetilde{h}$ defaults, the bank writes off the entire outstanding mortgage in period t, as the collateral value cannot be recovered immediately. Household deposits are not seized (i.e., mortgages are non-recourse in the model).[21]. The bank repossesses the house and attempts to sell it in period $t + 1$. When successful, the sales proceeds partially offset the capital loss

[21]This assumption reflects the fact that, while most European jurisdictions employ recourse systems, mortgage lenders still rely primarily on the collateral securing the loan to offset losses, while any offset against household deposits may not be automatic.

depending on house price dynamics.[22]

3.5 Central bank and capital requirements framework

The central bank performs two roles in the model; it acts as the system's settlement authority, and as the prudential regulator. It is modelled as a single agent and in its settlement function provides reserve balances that banks use to clear deposit transfers arising from transactions between their customers. These are needed when a household decides to consume from a firm associated with a different bank or when the household purchases a house from either a seller associated with a different bank or from a bank that is not the household's bank (e.g. when a bank sells a foreclosed house). In both cases, banks settle payments by adjusting their reserve accounts at the central bank. Reserves are also used to inject capital into banks when needed. Operationally, the central bank credits the reserve account of the recipient bank by the amount of the injection. On the bank's balance sheet, reserves and equity increase by the same amount. On the central bank's balance sheet, reserve liabilities increase and net worth declines correspondingly.

The central bank regulatory function shapes bank's credit supply through risk-based capital requirements. Although these requirements constrain banks' balance-sheet capacity, they do not generate any balance sheet transactions between the central bank and banks. Capital requirements are set as a share of banks' RWA, reflecting the prudential principle that different assets carry different levels of risk. The central bank, acting as the prudential authority, assigns risk weights to each asset class. It distinguishes three asset categories: reserves held at the central bank, mortgage loans to households, and loans to firms. Reserves are treated as risk-free, while loans to firms are treated as much riskier than household mortgages, reflecting the existence of collateral (see Appendix A for details). Given RWAs, the central bank requires banks to maintain their regulatory capital ratio at or above a minimum threshold:

$$CAR_{b,t} \geq CAR_t^{req},$$

where CAR_t^{req} denotes the regulatory capital requirement. This prudential constraint directly condi-

[22] This implies that the LGD for mortgage loans is set equal to one and any recovery from the subsequent sale of the repossessed property is recorded separately when the sale occurs. As a result, mortgage lending rates are somewhat higher than they would be if pricing were based on the net loss after collateral recovery. This simplification is unlikely to materially affect the results, as mortgage exposures are small relative to firms' working capital loans. However, it prevents us from capturing the procyclicality of mortgage LGDs through fluctuations in house prices. Incorporating realized collateral recoveries into LGD estimates is left for future research.

tions banks' credit supply and determines whether additional lending is feasible.

Regulatory capital requirements in the model can follow either a time-invariant framework or a time-varying framework that adjusts over the credit cycle. Given our objective of identifying the tail effects of a releasable buffer, we consider that the central bank can set regulatory capital requirements under two distinct regimes. In the first regime, banks operate under a time-invariant capital requirement (hereafter, TIP model), which remains constant throughout the credit cycle and serves as our benchmark for assessing the benefits and costs of introducing a releasable buffer. In the second regime, banks are subject to a time-varying capital requirement that fluctuates over the credit cycle (hereafter, TVP model).

3.5.1 Time-varying capital requirements regime.

Under this regime, banks are subject to a constant minimum requirement of 8% and to a time-varying releasable buffer, conceptually similar to the Countercyclical Capital Buffer (CCyB), denoted $CCyB_t$, that fluctuates over the credit cycle.[23] The required capital ratio therefore becomes:

$$CAR_t^{req} = 8\% + CCyB_t.$$

The buffer accumulation is based on a smoothed measure of real credit growth, defined as a 48-month exponential backward moving average ($CreditEBMA_t$). This smoothing approach filters out short-term volatility and highlights cyclical patterns that the central bank uses to inform the setting of the buffer. Specifically, the releasable buffer is set according to:

$$CCyB_t = \begin{cases} 0\%, & CreditEBMA_t < 6.5\%, \\ 0.185 \times (CreditEBMA_t - 6.5\%), & 6.5\% \leq CreditEBMA_t \leq 20\%, \\ 2.5\%, & CreditEBMA_t > 20\%. \end{cases}$$

[23] Macroprudential authorities in the EU have at their disposal multiple buffers. Even though the CCyB is the only buffer with releasable features in its design, macroprudential authorities recognise that other buffer like the sectoral systemic risk buffer could be used in a countercyclical way. So, the analysis presented here could be easily extended to consider the impact of certain time-varying sectoral capital policies.

rounded down to the nearest 0.25 percentage point and capped at 2.5% of RWAs, consistent with Basel III guidance.[24] According to this rule, when credit growth is modest (i.e. below 6.5%, which is the 50th percentile of the simulated distribution) the releasable buffer is set to zero. Credit growth below the median is interpreted as a normal (neutral) risk environment in our model. Once credit growth is equal or greater than 6.5%, the releasable buffer is set to a positive rate, increasing linearly as credit growth accelerates up to 20% (95th percentile of the distribution). The central bank reviews the buffer quarterly and any announced increase at time t is implemented after 12 months. This lag is consistent with Basel III guidance and is intended to give banks time to adjust to the higher requirements without imposing costs on the economy (e.g. restricting credit supply).

Buffer release is triggered when labour market conditions deteriorate, proxied by an increase in the three-month moving average of the unemployment rate.[25] Specifically, the buffer is set to zero when this indicator exceeds 5% (80th percentile of the unemployment distribution), a threshold indicating a recession. The immediate and full release of the buffer maximises its benefits as banks immediately increase their capital headroom, helping them continue lending or at least avoid sharply cutting credit supply. The objective of the time-varying capital requirement is to build resilience during upturns and to support lending conditions in downturns through buffer releasability. Subsections 5.2 and 5.3 examine the implications of this regime in downturns and upturns, respectively.

4 Empirical and economic validation

In this section, we conduct a set of exercises to assess the empirical validity of our parametrised benchmark model, i.e. the TIP model. Appendix C presents the values for all model parameters used in the simulations.

4.1 Empirical validation through moment matching

The model's simulated moments fall within plausible cross-country empirical ranges. We assess the empirical validity of the model by comparing simulated and empirical moments for three key macroeco-

[24]The coefficient 1.6 ensures a linear mapping from the credit growth range to a maximum buffer of 2.5% in the continuous version of the rule. The implementation in discrete 25 basis point steps is imposed separately by rounding down the resulting buffer to the nearest increment.

[25]Default rates could also be used as the indicator guiding the buffer release. However, in our model, default rates are highly correlated with the unemployment rate (see panel 4B in Figure 4), so using them would yield similar results.

nomic variables: annual growth rate of real GDP and real credit, and the unemployment rate.[26] The simulated moments are computed from 100 independent runs of the model, each spanning 1,500 monthly periods.[27] For each statistic, we average across the 100 runs to obtain a representative simulated moment. The corresponding empirical moments are obtained from quarterly data for all EU countries and the United States over the period 1999–2024 (see Appendix D for data details).[28] For each variable, we consider summary statistics that capture key features of their distributions: the mean, standard deviation, median, and the 25th and 75th percentiles.

Table 3 reports these moments and indicates whether the simulated statistic lies within the empirical range defined by the minimum and maximum values across countries. Cells highlighted in green denote that the model-generated moment falls within this empirical range, while amber shading indicates deviations. Despite its intentionally parsimonious structure, the model seems to reproduce the empirical moments of GDP and credit growth well (though less so for unemployment), suggesting a reasonable starting point for potentially calibrating the model to country-specific data. Appendix E presents the simulated moments values for a broader set of variables.

Table 3: Key macroeconomic variables: simulated vs empirical moments

	Mean	**Std. Dev.**	**p25**	**Median**	**p75**
Real GDP growth (%, p.a.)	Yes	Yes	Yes	Yes	Yes
Unemployment (%)	No	Yes	No	No	No
Real credit growth (%, p.a.)	Yes	Yes	Yes	No	Yes

Notes: Std. Dev. stands for standard deviation, p25 and p75 stand for the 25th and 75th percentiles, respectively, p.a. stands for per year. Real GDP and real credit are measured as annual growth rates. For each statistic, the yes(no) indicator reflects whether the average simulated moment (across 100 independent simulation runs of 1,850 monthly periods, with a 350-period burn-in), falls within (outside) the min-max range of its empirical cross-country equivalent. Empirical moments are computed using quarterly data for EU countries and the US between 1999 and 2024.

4.2 Cyclical properties of the model

The simulated economy captures expected cyclical co-movements, particularly the pro-cyclicality of credit and the countercyclicality of unemployment and default rates. To assess how well the model

[26] Inflation measures are excluded from the validation exercises because the model uses a stylised demand-driven pricing rule without calibrated sticky price dynamics. Consequently, nominal values cannot be matched consistently to observed data. More generally, the validation is intended as a generic empirical moment check and not a detailed, country level calibration.

[27] Each Monte Carlo simulation spans 1,850 monthly periods, with the first 350 periods discarded (20% of time-steps) to allow agents' balance sheets to stabilise and remove the effect of initial conditions. This simulation length provides a sufficient number of economic cycles for a robust analysis and ensures the model's statistical properties have stabilised, while keeping computations tractable.

[28] Data for the UK are included up to the point of the UK's withdrawal from the EU.

matches established stylised facts on cyclical behaviour, we analyse whether selected simulated variables move in the same direction as the business cycle (pro-cyclical) or in the opposite direction (countercyclical), following the approach of Stock and Watson (1999). The cyclical component of real GDP, extracted using the Hodrick-Prescott filter, is used as the reference business cycle indicator. For each variable x_t^i with $i \in \{1, \ldots, l\}$, we compute its cross-correlation with future and past values of the reference indicator, $\text{corr}(x_t^i, y_{t+k})$ for $k \in \{-12, 0, 12\}$, corresponding to a one-year lag, contemporaneous value, and one-year lead. Table 4 reports the results, with shading reflecting the strength of cross-correlation.

Table 4: Cross-correlations with real GDP of selected simulated variables

	t-12	**t**	**t+12**
Unemployment	-	-	-
Real credit	+	+	+
Default rate – Firms	-	-	-
Default rate – Households	-	-	-
Inflation	+	+	+

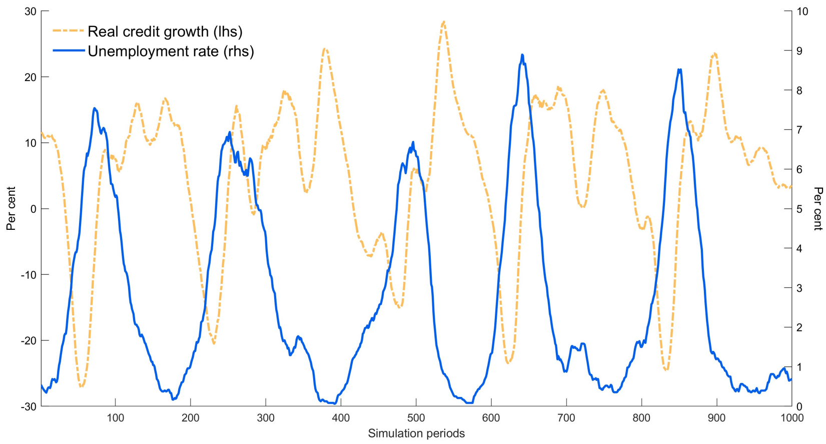
Notes: The table reports the sign of the average cross-correlations from 100 independent runs of the model of 1,850 monthly periods, discarding the first 350 periods as burn-in. Real GDP and real credit are expressed in logarithmic form and detrended using an HP filter with smoothing parameter of 129,600. Inflation is measured as annual growth rates. Lags (-) and leads (+) correspond to one year (12 simulations periods). A plus (minus) sign indicates a procyclical (countercyclical) relationship with the reference business cycle indicator. Cell shading indicates cross-correlation strength in absolute terms: light orange (0.5-0.7), medium orange (0.7-0.9), and dark orange (> 0.9).

A positive contemporaneous correlation ($k = 0$) indicates pro-cyclicality, whereas a negative one indicates countercyclicality. Inflation and real credit are procyclical, while the unemployment rate, and default rates are countercyclical. The strong contemporaneous correlation between real GDP and real credit reflects the credit-driven structure of the model. This is also consistent with empirical evidence that credit expands in booms and contracts in recessions. Stronger lagged correlations for some variables also reflect plausible macroeconomic patterns, such as gradual labour market adjustment and default risk responding to earlier GDP conditions and prolonged economic stress.

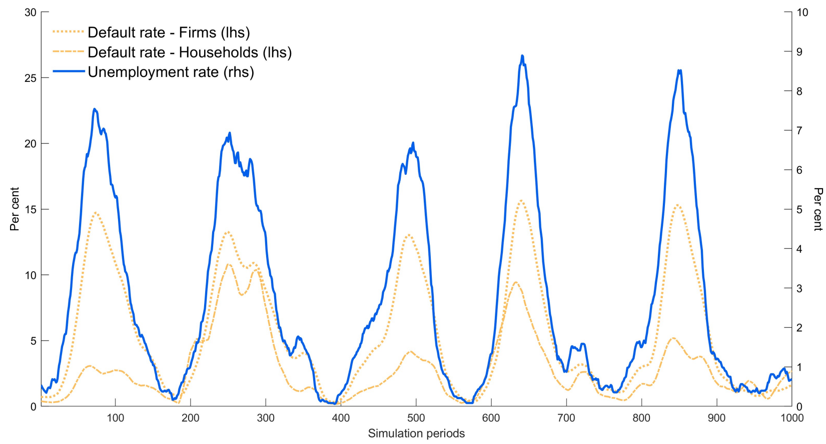
The simulated series exhibit clear cyclical patterns consistent with the cross-correlation results. Figure 4 illustrates the joint behaviour of real credit growth (panel A), default rates by borrower segment (panel B), against that of the unemployment rate, which serves as the proxy for the business cycle.[29]

[29] Using real GDP growth as the business cycle indicator, as in Table 4, leaves the results qualitatively unchanged.

Figure 4: Cyclical behaviour of key simulated variables



(A) Real credit growth



(B) Firm and household default rates

Notes: Simulated variables are obtained from a single run of the model over 1, 850 monthly periods. All series are smoothed using a moving average approach.

Consistent with the cross-correlation patterns, real credit growth displays a strong negative relationship with unemployment: periods of rising credit growth tend to precede decreases in unemployment. In contrast, both firm and household default rates move closely with the unemployment rate, exhibiting a strong positive and largely contemporaneous relationship. All variables exhibit pronounced cyclical fluctuations and firm default rate is noticeably higher than household default rate during downturns. These patterns are in line with well-documented empirical regularities (Ivashina et al., 2024; European Central Bank, 2025; European Banking Authority, 2025). Overall, the model's replication of a set of key empirical regularities, including matching selected statistical moments and expected cyclical relationships between economic variables, supports its reliability as a framework for studying the state-contingent effects of a releasable buffer.

5 Policy experiments

This section sets out the policy evaluation strategy used to assess the state-contingent tail costs and benefits of a time-varying releasable buffer and discusses the main results.

5.1 Policy experiment design

Policy experiments evaluate the tail costs and benefits of introducing a time-varying, releasable capital buffer by comparing distributions of key macro-financial variables between alternative capital requirement regimes. We use the DeTail model to conduct two policy experiments that evaluate the tail costs and, respectively, benefits of a releasable buffer, which fluctuates over the credit cycle. In both experiments, we compare the distribution of selected variables under a benchmark model with time-invariant capital requirements (TIP model) to those generated by a model with a time-varying, releasable buffer (TVP model). The variables of interest include real credit growth, default rates by borrower segment, and bank losses.

The analysis evaluates policy costs and benefits separately during upturns and downturns of the credit cycle. Downturns are defined as periods when the unemployment rate exceeds its 80th percentile, capturing times of heightened stress in the real economy. Upturns are the complementary periods outside of these high-unemployment episodes. Because costs and benefits arise at different phases of the credit cycle, we assess the policy effects separately for upturns and downturns. Specifically, policy effectiveness is evaluated through: (i) improvements in the policy-relevant tail of each variable's distribution, capturing whether severe outcomes become less severe; (ii) changes in dispersion, measured by the interquartile range of the distribution; and (iii) shifts in probability mass near the tails, reflecting changes in the likelihood of extreme events.

The tail benefits of releasable buffers arise during economic downturns as an improvement in the policy-relevant tail of the distribution of the outcome variable under the TVP model relative to the TIP model. The definition of improvement is contingent on whether an increase or decrease in the outcome variable is the desired policy impact, from a systemic risk reduction perspective. Policy driven benefits can be represented by increases in the lower-tail (also negative) percentiles of a variable (e.g. credit growth) under a releasable buffer relative to a time-invariant capital requirement regime.[30] They may also take the form of decreases in the higher-tail percentiles of a variable (e.g. sectoral default rates). Conversely, the tail costs of releasable buffers are identified during upturns. Any costs are reflected in a deterioration of the policy-relevant tail percentiles, a widening of the interquartile range, or an increase in the probability mass around the extreme tails.

We further examine the policy's effects on banking-system resilience and on the amplitude and duration of the endogenous credit cycles. Although our model abstracts from the macroeconomic feedback effect of bank default, we can nevertheless gauge changes in the implicit cost of bank default by tracking the need for central bank interventions. A lower frequency or size of such interventions in the TVP model relative to the TIP model would indicate improvements in banking system resilience even in the absence of formal defaults. Such results are consistent with a policy induced systemic risk reduction; therefore, we include them as part of the assessment of the tail benefits of a releasable buffer.

Finally, because the DeTail model generates endogenous credit cycles, we are also able to assess the effects of a releasable buffer on credit cycle dynamics. Following Drehmann et al. (2012), we evaluate whether introducing a releasable buffer in the mix of capital requirements affects the amplitude and duration of credit expansions and contractions (for example, whether contractions become shorter or less severe under the TVP regime compared to the TIP regime).

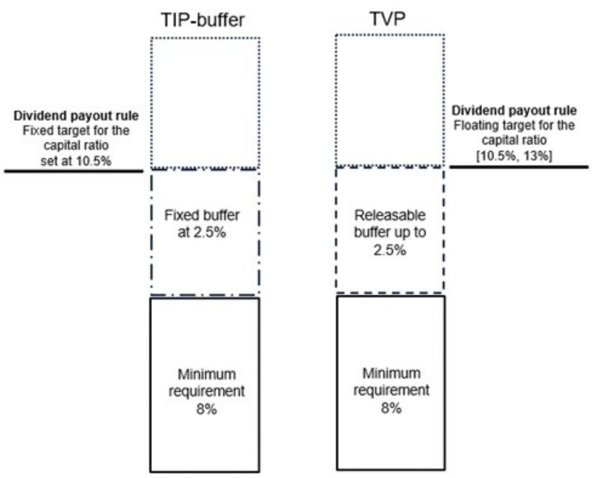
5.2 Assessing the benefits of a releasable buffer in downturns

Tail benefits of releasable buffers emerge during economic downturns, when easing capital constraints can mitigate severe outcomes. The first policy experiment focuses on the tail benefits of releasing a capital buffer by comparing the distributions of key variables under the TIP model and the TVP model during economic downturns. In the TIP model, banks are subject to a minimum capital requirement of 8% plus a fixed buffer of 2.5%, which applies throughout the credit cycle (TIP-buffer model). In the TVP model, banks are subject to the same minimum requirement but face a buffer that varies over the credit cycle. Dividend payout decisions are governed by a target capital ratio linked to capital requirements (see Appendix A for details). Under the TIP model, this target is fixed at the regulatory

[30] An improvement in the lower tail of credit growth means that the bottom percentiles of the distribution are higher (either positive or less negative) as a result of releasing the buffer, reflecting milder credit contractions during a downturn.

requirement of 10.5%, whereas in the TVP model it starts at 10.5% when the releasable buffer is zero, and then increases proportionally as the buffer accumulates. In general, because banks anticipate future increases in time-varying capital buffers but cannot foresee their timing, they typically maintain capital ratios above regulatory requirements by adjusting, for instance, dividend payouts. Our specification of a target capital ratio that moves with the releasable buffer, while starting at the TIP level, replicates this behaviour. Figure 5 illustrates the capital stack and associated dividend-payment thresholds in both settings. This setup ensures that banks in both model simulations face the same capital requirements at the peak of the credit cycle, so any differences in downturn outcomes can be attributed to the effects of buffer releasability.

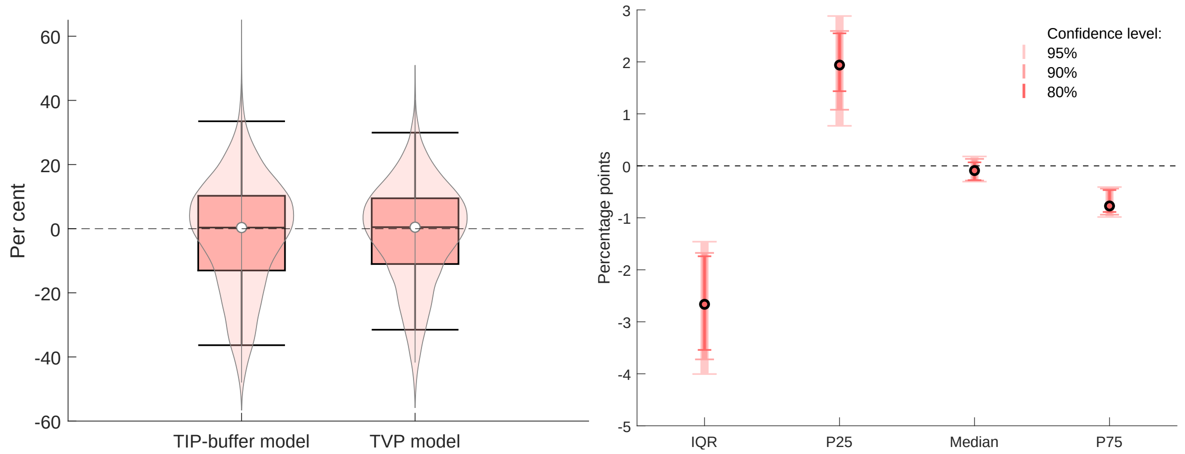
Figure 5: Components of capital ratios in the TIP-buffer and TVP models



Notes: The solid outline box denotes the minimum capital requirement of 8%. In the TIP-buffer model (left capital stack), the dash-dotted outline marks the fixed 2.5% buffer. In the TVP model (right capital stack), the dashed outline indicates the time-varying releasable buffer, which can reach up to 2.5%. The dotted outline box represents capital held in excess of the total requirement (minimum requirement plus the applicable buffer).

The release of capital buffers during downturns yields notable improvements in the tail of credit dynamics. Panel A of Figure 6 presents the simulated distributions of real credit growth during downturn periods under the TIP-buffer and TVP models, based on 100 Monte-Carlo simulations of 1,850 monthly periods each, with the first 350 periods discarded as burn-in. All downturn observations across simulations are pooled to construct the distributions. Panel B reports bootstrap-based confidence intervals for the difference in selected distributional statistics between the two regimes, namely, the interquartile range (IQR) and the 25th, 50th, and 75th percentiles, computed from 10,000 resamples of the model-by-model differences.[31] This statistical assessment complements the economic interpretation by indicating whether observed differences are distinguishable from zero. This approach represents, to our knowledge, the first application of such inference to policy experiments involving capital buffers in an agent-based model.

Figure 6: Real credit growth in downturns: TIP-buffer vs TVP models



(A) Distributions (B) Confidence intervals

Notes: Panel A shows the distribution of simulated real credit growth during downturn episodes, based on 100 Monte-Carlo simulations of each model. Each simulation spans 1,850 monthly periods, with the first 350 periods discarded as burn-in. Real credit growth is measured as an annual rate. Boxplots display the 25th percentile, median, and 75th percentile, with whiskers indicating values within 1.5 times the interquartile range, excluding outliers; shaded areas show the kernel density estimate of the distribution of pooled real credit growth in downturns (Gaussian kernel, bandwidth selected using Silverman's rule). Panel B reports bootstrap-based confidence intervals for selected statistics. For each statistic, the difference between models is computed for every run and resampled 10,000 times with replacement. Confidence intervals, centred around the median of the bootstrap distribution, are shown at the 80%, 90%, and 95% levels. IQR stands for interquartile range, P25 and P75 stand for the 25th and 75th percentiles, respectively.

Results show that releasing the buffer in downturns improves the lower (riskier) tail of real credit growth, by shifting it upward relative to the TIP-buffer model. The 25th percentile of real credit growth is approximately 2 percentage points (p.p.) higher (equivalent to a 15.7% improvement in the lower tail). The IQR is about 2.7 p.p. narrower (equivalent to a 12.1% reduction), indicating lower volatility in real credit growth in downturns. Finally, the probability mass in the riskier lower tail is reduced. These notable economic effects are statistically significant at conventional confidence levels. Taken together, our results suggest that the TVP regime delivers more stable credit conditions when the economy is under stress, consistent with the intended objectives of the policy.

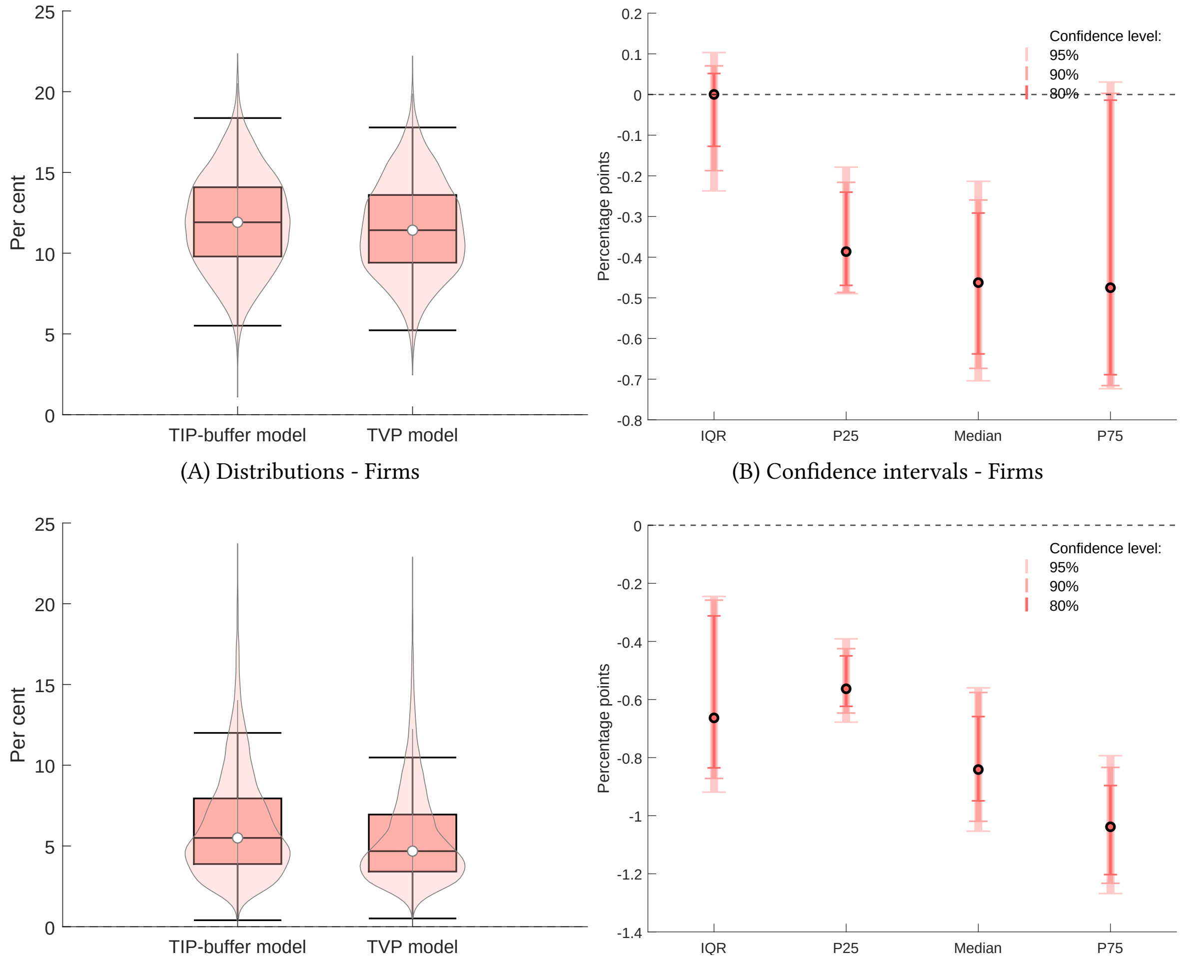
[31] These intervals are centred on the median difference between models because the bootstrap distributions of some statistics are skewed, making the median a more representative measure of the typical difference than the mean.

Household and firm default rates also improve under a releasable buffer. Figure 7 presents the same set of results for default rates by borrower segment, with panels A and C displaying the distributions and panels B and D reporting confidence intervals for the differences between the TIP-buffer and TVP models. The release of the buffer reduces default rates in the upper riskier tail of the distribution by 0.7 p.p. for firms and 1.2 p.p. for households. However, this reduction is statistically significant only at the 80% confidence level for firms, whereas it is statistically significant across all confidence levels for households. In our model, the effectiveness of a releasable buffer in mitigating credit risk is more robust in the household sector. The more muted response among firms reflects two offsetting forces. While the buffer release supports loan demand and helps reduce firm closures in the model, it also allows firms to obtain additional financing, raising leverage and increasing their vulnerability in subsequent periods. As a result, the net improvement in firm-sector default risk is more limited, though importantly, it does not worsen. As for volatility, the interquartile range of firm default rates remains broadly unchanged under the TVP model relative to the TIP-buffer model, whereas households exhibit a statistically significant reduction. Finally, the likelihood of extremely high default rates declines in both sectors in the presence of a releasable buffer, with the effect again stronger for households.

Buffer release during downturns supports the economy without compromising banking system resilience. Reflecting the improvement in the loan portfolio's risk profile, the upper tail of the bank loss distribution declines by 0.9 percentage points relative to the TIP-buffer model (see Figure 8), corresponding to a reduction of 4.8%. This indicates a reduced likelihood of very large bank losses during downturns, mitigating the potential for negative spillovers from the banking system to the real economy that could exacerbate downturns. This decline is statistically significant across all conventional confidence levels. Although the interquartile range is only modestly narrower and not statistically significant, it still points to slightly more stable loss dynamics when the buffer is released. Overall, these findings suggest that expanding credit availability via the release of the buffer in downturns to support the economy does not exacerbate banks' default risk.

Capital injections become smaller and less frequent under a releasable buffer, indicating greater banking-system resilience during downturns. To complement the analysis on bank losses, Figure 9 shows the frequency of capital injections during economic downturns, disaggregated by the number of banks receiving support. An x-axis value of zero indicates that no bank required a capital injection,

Figure 7: Firms and household default rates in downturns: TIP-buffer vs TVP models



(A) Distributions - Firms

(B) Confidence intervals - Firms

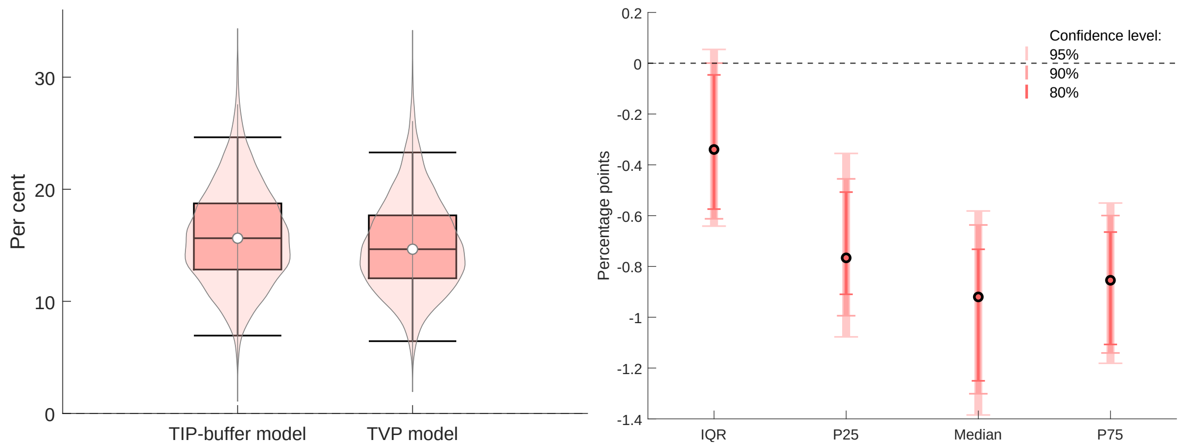
(C) Distributions - Households

(D) Confidence intervals - Households

Note: See the notes to Figure 6 for details on the distributions and confidence intervals.

which means that all banks remained solvent. The release of capital buffers is associated with a lower incidence of interventions relative to a regime with time-invariant requirements. When capital injections do occur, they typically involve a smaller share of the banking sector under the TVP model. In the latter model, most downturn periods require support for only one or two banks, whereas under the TIP-buffer regime, interventions commonly span from one up to three banks. Figure 10 further shows that the size of interventions is also lower when a releasable buffer is in place. The upper percentile of the distribution of capital injections under the TVP model is 1.2 p.p. (16.3%) below that of the TIP-buffer model, implying that sizeable interventions by the central bank are rarer when buffers can be released. This suggests that the banking system is more capable of withstanding economic stress under the TVP regime, as the buffer release provides additional credit to firms, reducing closures, and supporting income by preventing a rise in unemployment. The improvement in the size of capital injections is statistically significant.

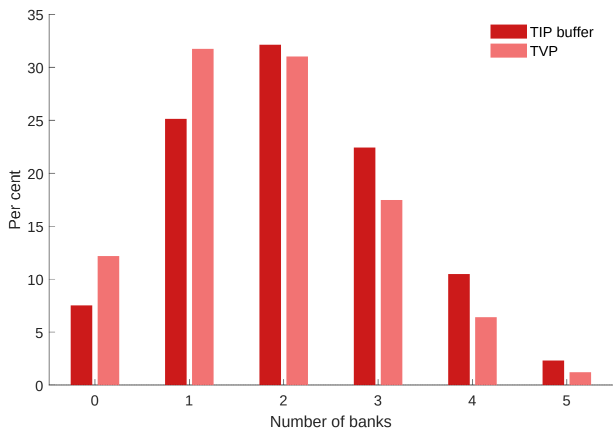
Figure 8: Bank losses in downturns: TIP-buffer and TVP models



(A) Distributions (B) Confidence intervals

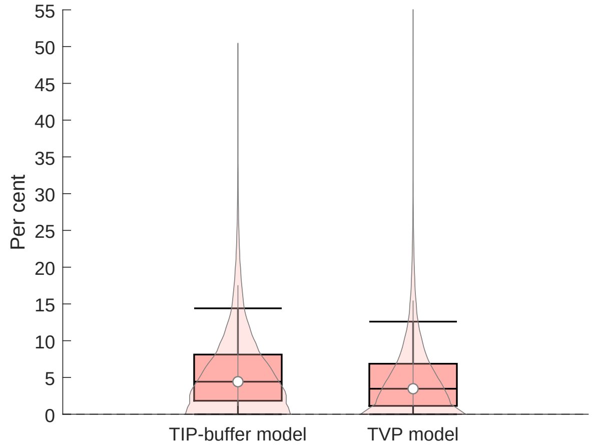
Note: Bank losses are measured as the product of default rates and loss-given-default for firms and households. See the notes to Figure 6 for details on the distributions and confidence intervals.

Figure 9: Frequency of capital injections in downturns: TIP-buffer vs TVP models

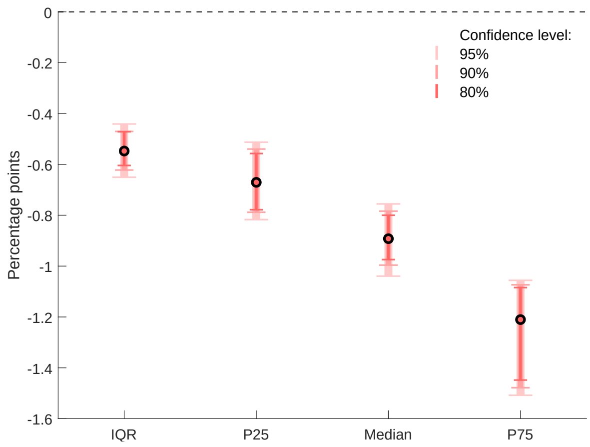


Note: Capital injections refer exclusively to interventions aimed at preventing bank defaults by restoring banks' capital ratios above the regulatory minimum. An x-axis value of zero indicates that no bank required a capital injection to remain solvent.

Figure 10: Capital injections in downturns: TIP-buffer vs TVP models



(A) Distributions



(B) Confidence intervals

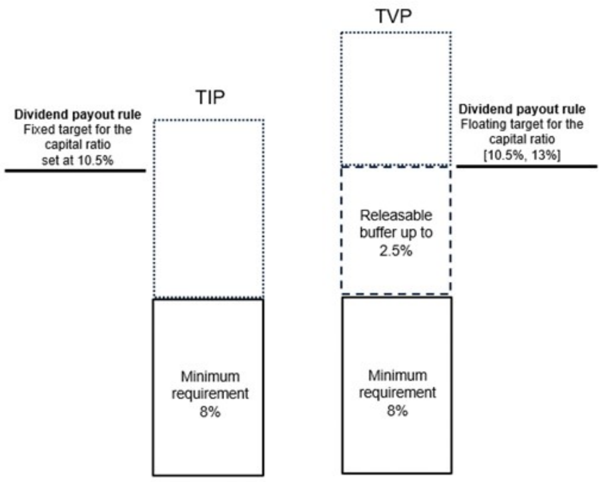
Note: Capital injections refer exclusively to interventions aimed at preventing bank defaults by restoring banks' capital ratios above regulatory minimum. Capital injections are expressed as a percentage of output. See the notes to Figure 6 for details on the distributions and confidence intervals

In addition to the main variables analysed, we also find modest improvements in other macroeconomic outcomes when the buffer is released in a downturn, including a slight downward shift in the median and lower quartile of unemployment and a reduction of downside risks (riskier tail) to house price growth. Additional evidence on these variables is reported in Appendix B. These effects are either economically small or, in the case of house prices, should be interpreted cautiously given the challenges in matching the empirical inflation level.

5.3 Assessing the costs of a releasable buffer in upturns

Tail costs associated with buffer accumulation, if present, would materialise during economic upturns. The second policy experiment evaluates the potential tail costs associated with building a releasable capital buffer, which may emerge during economic upturns when such buffers are typically accumulated. To investigate these costs, we compare the distribution of simulated variables under a TIP model with only the minimum capital requirement to that under the TVP model used in the first policy experiment. Figure 11 illustrates the two capital regimes used. Although capital requirements differ between the two models at the peak of the credit cycle, both begin each upturn with identical requirements. This ensures that any divergence in outcomes during the accumulation phase can be attributed to the build-up of a releasable buffer. The dividend payout rule remains the same as in the downturn analysis, ensuring comparability across policy regimes.

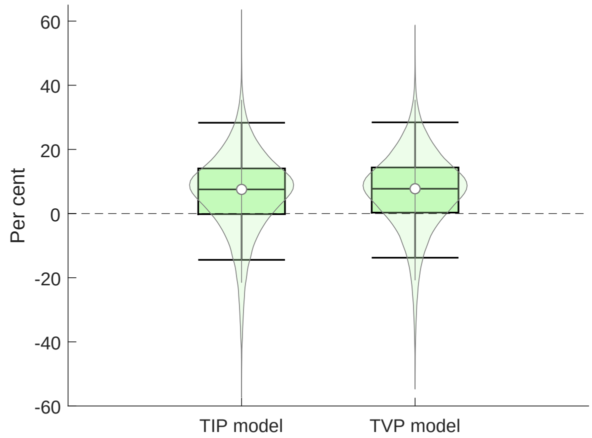
Figure 11: Components of capital ratios in the TIP and TVP models



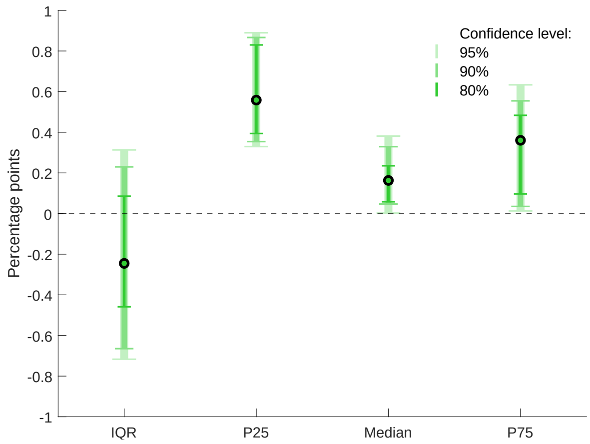
Note: The solid outline box denotes the minimum capital requirement of 8%. In the TVP model (right capital stack), the dashed outline indicates the time-varying releasable buffer, which can reach up to 2.5%. The dotted outline box represents capital held in excess of the total requirement (minimum requirement plus the buffer, if applicable).

Buffer accumulation during economic upturns does not materially alter credit dynamics. Panel A of Figure 12 displays the distributions of real credit growth during upturns for both the TIP and TVP models, while Panel B reports the confidence intervals for the differences in key distributional statistics. Apart from the applicable capital requirements in the TIP model, these results draw on the same model simulations used in the first policy experiment. Relative to the TIP regime, the distribution of real credit growth under the TVP model remains broadly unchanged. Nonetheless, there is a mild improvement in the lower risky tail of the distribution, and some reduction in the incidence of extreme outcomes. These findings suggest that the presence of a releasable buffer does not constrain credit growth during economic upturns. The underlying mechanism is that the reduction in credit supply, triggered only during periods of unusually strong credit growth within upturns, is not large enough to impede the banking system from meeting aggregate credit demand.

Figure 12: Real credit growth in upturns: TIP vs TVP models



(A) Distributions

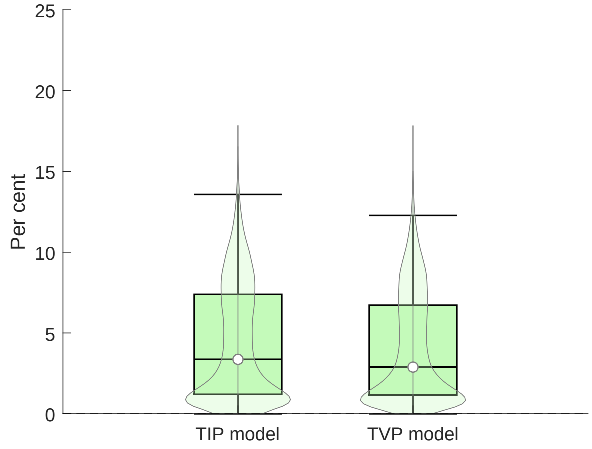


(B) Confidence intervals

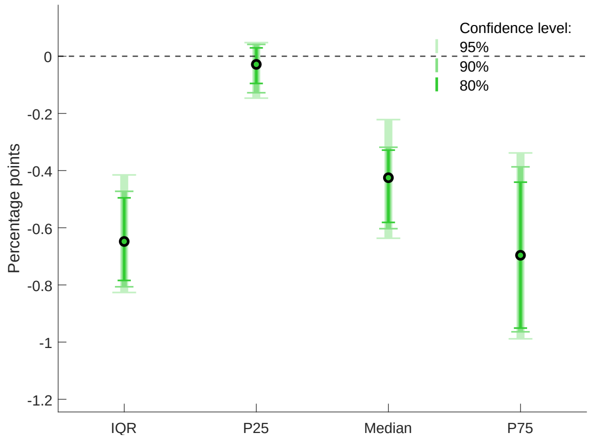
Note: See the notes to Figure 6 for details on the distributions and confidence intervals.

Default-risk dynamics in expansions show no evidence of tail costs from buffer accumulation, with tail improvements for firms and no meaningful effects for households. Panel A of Figure 13 shows an improvement in the upper tail of firm default rate, indicating that worst-case default rates are lower under the TVP model than under the TIP model. This reduction is statistically significant (see panel B). Two mechanisms drive this result. First, as banks accumulate the releasable buffer, they moderate credit supply relative to the TIP model. Second, this reduction occurs under a risk-based allocation rule that prioritises lending to less-leveraged firms, thereby limiting credit to more vulnerable, highly leveraged firms, more likely to default in future. By curbing credit to these riskier borrowers, the overall risk profile of the credit portfolio improves, resulting in a lower upper tail firm default rates and reduced volatility. In contrast, the distributions of household default rate remain largely unchanged (see panels C and D in Figure 13).

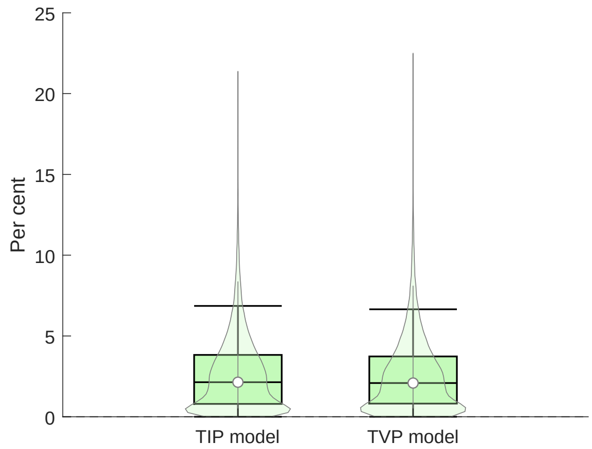
Figure 13: Firm and household default rate in upturns: TIP vs TVP models



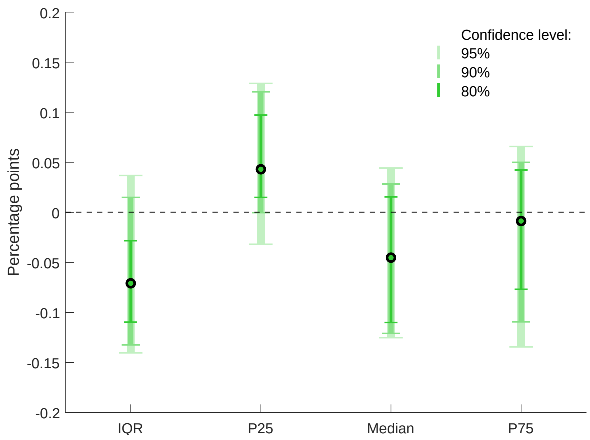
(A) Distributions - Firms



(B) Confidence intervals - Firms



(C) Distributions - Households

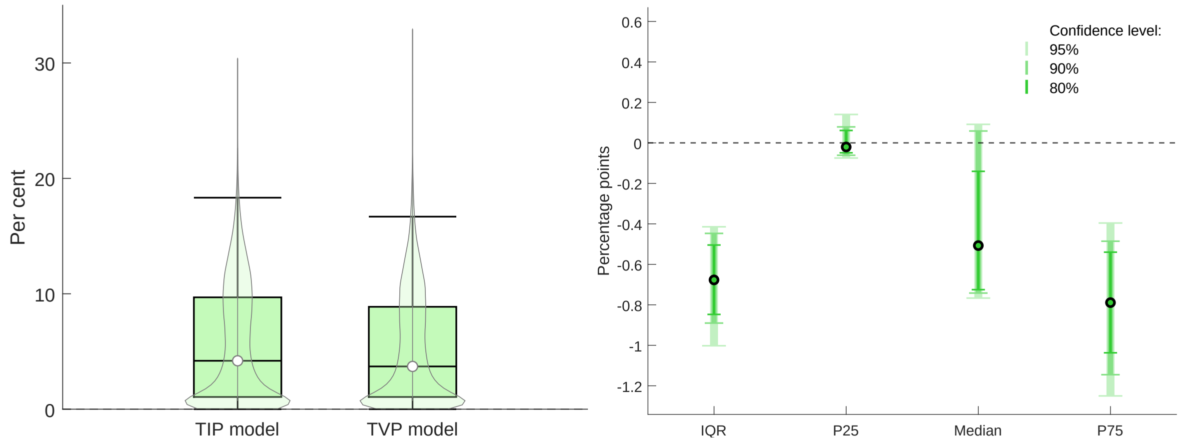


(D) Confidence intervals - Households

Note: See the notes to Figure 6 for details on the distributions and confidence intervals.

Finally, the accumulation of a releasable capital buffer during expansions does not materially change the distribution of bank losses (see Figure 14). Nevertheless, there is a statistically significant reduction in the upper tail and volatility, consistent with the improvement in firm-sector default risk. Overall, these results indicate that the resilience of the banking system is not negatively affected by the building up of the buffer. This pattern also carries over to broader macroeconomic outcomes. The unemployment rate is broadly unchanged to slightly improved under the TVP regime, while house price growth shows limited differences across most of the distribution, with some evidence of stronger growth in favourable states. Further results are reported in Appendix B.

Figure 14: Bank losses in upturns: TIP vs TVP models



(A) Distributions (B) Confidence intervals

Note: Bank losses are expressed as the default rate times loss given default of firms and households. See the notes to Figure 6 for details on the distributions and confidence intervals.

5.4 Assessing the effects of a releasable buffer on credit cycle dynamics

Releasing the buffer reduces the median duration and modestly dampens the amplitude of the credit cycle. The effects are particularly pronounced during contractions, which become notably shorter in duration and exhibit a decline in amplitude. Having assessed the state-contingent tail costs and benefits, we now evaluate the impact of a releasable buffer policy on the duration and amplitude of the credit cycle. To do so, we apply the turning point methodology as in Drehmann et al. (2012) to identify medium-term peaks and troughs in our simulated credit series. Table 5 shows the median duration and amplitude of the credit cycle during both phases of the credit cycle (expansions and contractions) across the TIP and TVP regimes.[32] Consistent with the empirical evidence, the contraction phase in the credit cycle is significantly shorter than the expansion phase in both models. More importantly, the credit cycle under the TVP model shows a notably shorter median contraction by two quarters relative to the TIP model, while the expansion phase shortens only marginally (by less than one quarter). As a result, the overall median cycle duration is slightly lower under the TVP regime. The amplitude of both expansions and contractions also declines, although these effects appear modest and similar between cyclical phases.

[32]Duration and amplitude in expansions is measured from trough to peak and in contractions from peak to trough.

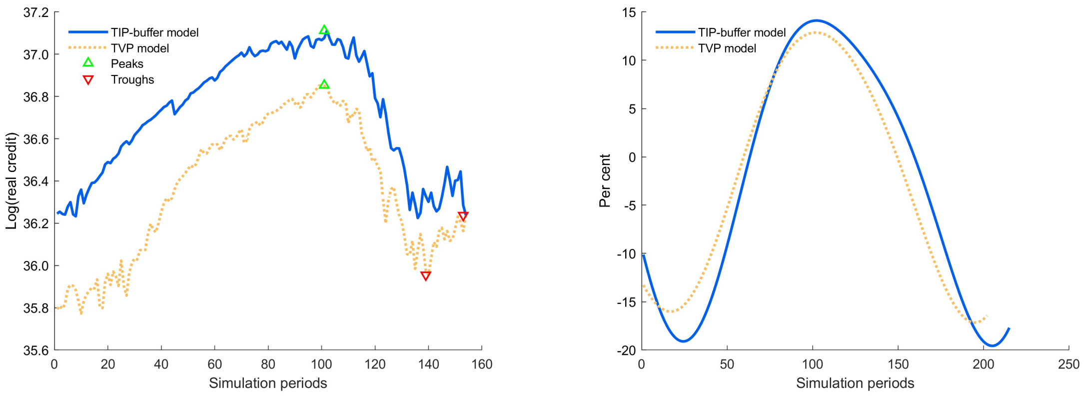
Table 5: Turning point analysis of simulated credit series

	Median duration		Median amplitude	
	Expansion	**Contraction**	**Expansion**	**Contraction**
Real credit – TIP model	13.8	4.0	1.5	-0.8
Real credit – TVP model	13.6	3.5	1.4	-0.7
Difference (TVP-TIP)	-0.2	-0.5	-0.1	0.1

Note: The turning point methodology of Drehmann et al. (2012) is applied to the simulated log level of real credit to identify medium-term credit cycles. Both the TIP and TVP models are simulated for 8,000 monthly periods. Peaks and troughs are identified based on the following rules: a) window length 9 quarters (27 months) with a peak (trough) identified if the change in the variable is positive (negative) at predetermined lags and leads, b) the minimum length of the cycle is set to 5 years (60 months) and that of each phase (expansion/contraction) to 2 quarters (6 months). Manual adjustment was occasionally needed, with the additional application of the Christiano-Fitzgerald bandpass filter serving as complementary analysis (see Figure 15). Cycle duration is measured in years and amplitude in percent changes.

Figure 15 complements the results in Table 5 by providing a visual representation of the effects of a releasable buffer on credit cycle dynamics. The left panel aligns representative peaks, identified using the turning point analysis, from one TIP cycle and one TVP cycle. This comparison helps to identify that the contraction phase is notably shorter under the releasable buffer approach. The right panel plots the Christiano–Fitzgerald filtered credit cycles for one selected cycle episode in each regime.[33] The comparison shows that the amplitude of the credit cycle is modestly lower under the TVP model relative to the TIP model, supporting the earlier finding.

Figure 15: Cycle windows



(A) Turning point approach (B) Frequency-based approach

Note: Panel A aligns representative peaks, identified using the turning point methodology, for one TIP cycle and one TVP cycle. Panel B presents the Christiano–Fitzgerald filtered credit cycles for a selected episode under each regime. The filter is applied to the annual growth rate of real credit, retaining cycles with a duration between 32 and 120 quarters (or, equivalently, between 96 and 360 months).

[33] The turning-point approach and the Christiano–Fitzgerald (CF) filter are employed as complementary methods for extracting the medium-term credit cycle, following the practice in Drehmann et al. (2012).

6 Conclusion

This paper introduces the DeTail agent-based (ABM) framework to assess macroprudential policies. The economy features heterogeneous firms, households, banks, and a single central bank interacting across production, labour, consumption, housing, and credit markets. These interactions generate a credit-driven macroeconomy that endogenously generates standard cyclical dynamics and is suitable for analysing macroprudential policies. The model extends the stock-flow consistent agent-based framework of Gross (2022) in three significant directions by introducing a housing market and mortgage lending, multiple banks subject to risk-based capital requirements, including both minimum capital requirements and buffers, and a central bank. An essential strength of our ABM framework is the simulation of full distributions of key variables of interest based on heterogeneous agent interaction.

We use the DeTail framework to analyse the state-contingent tail effects of a releasable macroprudential capital buffer. A first policy experiment isolates the tail benefits of buffer release when economic conditions deteriorate, while the second assesses the potential tail costs associated with buffer accumulation during upturns. In both experiments, we compare the simulated distributions of key variables, such as credit growth, borrower-segment default rates, and bank losses, under a fixed capital requirement regime and under a regime with time-varying capital requirements.

We find that releasing the macroprudential capital buffer provides clear tail benefits during downturns. When economic conditions deteriorate, easing macroprudential capital requirements helps preserve credit supply and reduces the volatility of credit growth. This results in significantly better outcomes: severe credit contractions are less pronounced, and the upper (riskier) tails of firm and household default rate distributions decrease. Importantly, these gains are achieved without weakening banking sector resilience. We also find that building-up macroprudential buffers during upturns does not generate significant costs. The distribution of credit growth remains effectively unchanged when banks are required to build up capital during upturns, indicating that tighter requirements do not significantly constrain lending in good times. Moreover, by curbing credit to the riskiest borrowers, higher requirements yield slight improvements in the upper tail of firm default rate. We also find no adverse impact on bank loss distribution. Overall, our policy experiments confirm that introducing a releasable buffer in the capital mix supports the continued provision of credit during downturns at little cost during upturns and without compromising banking system resilience. Consistent with this, we also find that a releasable buffer improves the dynamics of the credit cycle by reducing its median duration and modestly dampening its amplitude.

Our ABM approach is directly relevant for systemic risk analysis and macroprudential policies, which are particularly concerned with tail risks. The development and application of DeTail complement the existing literature on the costs and benefits of releasable buffers by generating cross-section, time-varying distributions of key variables, supporting a more granular, state-contingent, and tail-focused assessment of macroprudential policy effectiveness. Taken together, these results provide strong support for the timely build-up and active use of a releasable capital buffer throughout the cycle. Our results show that macroprudential capital buffers help to contain the most adverse outcomes of credit cycles without creating drag during upturns or weakening banking system resilience, fully aligning with the policy's intended objectives.

Additional model extensions, such as the inclusion of a positive neutral rate rule for the CCyB and other (sectoral) macroprudential buffers, including more detailed calibrations to reflect potential specificities at the country level are left for future research.

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A Additional model details

Household behaviour

Consumption smoothing. When a household sells its house, the resulting increase in its deposit balance represents a temporary positive wealth shock. To avoid an unrealistically sharp rise in consumption, the model imposes a consumption-smoothing rule instead of the standard MPC rule to this unusually large inflow. Specifically, household consumption after a house sale is given by:

$$c_{h,t} = (1 + v) \times \tilde{C}_{t-1}$$

where $\tilde{C}_{t-1}$ represents the economy-wide average consumption level in period $t-1$ and v is the smoothing parameter. Under this rule, the additional deposits from the sale are gradually drawn down, with the duration of the drawdown determined by the choice of v. In the baseline parametrisation (see Appendix C), this implies full depletion after 60 periods, at which point the standard consumption rule is resumed. This behaviour is consistent with the permanent income hypothesis: households treat the sale proceeds as transitory wealth and smooth consumption accordingly rather than consuming the full amount immediately.

Bank behaviour

Interbank payments. When a household whose deposit account is held at bank b_1 purchases goods from a firm banking with bank b_2, the payment associated with this consumption flow is settled through an interbank reserve transfer. The settlement occurs through the central bank: an equivalent amount of reserves is debited from bank b_1's reserve account and credited to bank b_2 reserve account. Although firms and households do not change banks, payments across banks cause interbank reserve transfers managed by the central bank's clearing mechanism (see subsection 3.5 for details on the central bank's role in the model).

Capital injections to satisfy minimum credit supply. The required capital injection for bank b in period t, denoted $CI_{b,t}$, is the amount needed to restore compliance with capital requirements after extending the additional firm loans implied by the minimum credit supply rule. Formally,

$$CI_{b,t} = \left(\sigma \times rw^{F} \times WB_{b,t} + RWA_{b,t}\right) CAR_t^{\text{req}} - NW_{b,t}.$$

where, rw^F is the risk weight assigned to firm loans in the capital requirements framework. The first term in parentheses represents the risk-weighted assets (RWA) associated with the additional required loans, while the second term captures the bank's existing RWA. Multiplying their sum by the regulatory capital ratio yields the total capital required to support the combined portfolio, and subtracting current net worth gives the resulting capital shortfall. A capital injection immediately increases bank equity and expands lending capacity. Following an injection, the bank's available credit supply is recalculated using the higher capital position.

Consolidation of multiple firm loans. When a firm with an existing loan takes a new working-capital loan, the model combines the two into a single composite loan for the purposes of interest and maturity calculations. The composite interest rate, $I_{f,t}$, and remaining maturity, $D_{f,t}$, are calculated as loan-size-weighted averages of the previous and new loan terms:

$$I_{f,t} = \frac{L_{f,t-1} \cdot I_{f,t-1} + l_{f,t} \cdot i_t^F}{L_{f,t-1} + l_{f,t}}$$

$$D_{f,t} = \frac{L_{f,t-1} \cdot D_{f,t-1} + l_{f,t} \cdot d_{f,t}}{L_{f,t-1} + l_{f,t}}$$

If the firm has no prior loan, $L_{f,t-1} = 0$, the composite loan simply inherits the terms of the new loan.

Loan pricing rule. Banks price loans based on expected segment-level credit risk and funding costs. At origination, bank b sets the interest rate for borrower segment $j \in \{H, F\}$ so that the expected return on the loan equals the expected cost of funds:[34]

$$PD_t^j \times LGD_t^j + \left(1 - PD_t^j\right)\left(\mu - i_t^M\right) = \left(1 - PD_t^j\right) i_t^j.$$

which yields

$$i_t^j = \mu + i_t^M + \frac{PD_t^j \times LGD_t^j}{1 - PD_t^j}, \qquad j \in \{H, F\}.$$

Credit risk expectations. The time-varying credit risk premium in the loan pricing rule is a function of the bank's expectations about aggregate probability of default (PD_t^j) and loss given default (LGD_t^j)

[34]Both the probability of default (PD) and loss given default (LGD) used in the loan pricing rule are smoothed using a 15-period moving average, following Gross (2022). This approach mitigates short-term volatility and ensures more stable estimates for loan pricing.

within each borrower segment. Banks update PD_t^j based on observed default flows:

$$PD_t^j = \frac{\sum_j \text{DefaultFlow}_{j,t-1}}{1 - L_t^j}$$

This assumes that the best estimate for the likelihood a loan will default is the proportion that defaulted last period adjusted for the loan portfolio. Expected loss given default differs by loan segment. For firm loans:

$$LGD_t^F = \frac{\sum_{k\in F} \left(\text{DefaultFlow}_{k,t-1} - \text{seize}_{k,t}\right)}{\sum_{k\in F} \text{DefaultFlow}_{k,t-1}}$$

reflecting deposit seizure upon firm default. For household mortgages, $LGD_t^H = 1$, as deposits are not seized to cover losses.

Setting the interest rate based on the aggregate credit risk at borrower segment level, rather than using the borrower's specific credit risk, introduces a friction in the model that reflects either the cost of monitoring for banks or informational asymmetries faced by banks.

Dividend distribution mechanism. The target capital ratio depends on the capital requirements regime introduced in subsection 3.5. Under time-invariant capital requirements, the target does not vary over the credit cycle and is set equal or above the requirement. Under time-varying requirements, the target rises and falls with the buffer, ensuring banks avoid breaching requirements throughout the cycle.

Dividends are distributed equally among all households that are depositors of that bank. Each receives $\frac{div_{b,t}}{n_H}$ as dividend income. Dividend income increases households' deposit balances and is used for debt servicing or future consumption but does not affect current consumption (see subsection 3.3).

Debt servicing. At the end of each period, every borrower calculates a fixed annuity payment

$$a_{j,t} = a_{j,t}^I + a_{j,t}^D, \qquad j \in \{f, h\},$$

where $a_{j,t}^I$ and $a_{j,t}^D$ stand for the interest component of the payment and for the principal amortisation component, respectively. The annuity payment is given by the standard instalment-loan formula:

$$a_{j,t} = \frac{D_{j,t} \times I_{j,t} \left(1 + I_{j,t}\right)^{D_{j,t}}}{\left(1 + I_{j,t}\right)^{D_{j,t}} - 1}, \qquad j \in \{f, h\}.$$

Depending on the borrower's available resources, $M_{j,t}$, one of three cases applies:

- *Regular amortisation:* If the borrower has sufficient deposits to cover the full annuity, $M_{j,t} \geq a_{j,t}$, it pays the full amount.
- *Interest-only payment:* If the borrower's deposits are sufficient to cover the interest but not the full annuity, i.e. $a_{j,t} \geq M_{j,t} \geq a^I_{j,t}$, the borrower pays interest only and the unpaid principal is rolled over and added to next period's obligations.
- *Default:* If the borrower cannot cover the interest due, i.e. $a_{j,t} \geq a^I_{j,t} > M_{j,t}$, then it defaults on the loan. Because partial interest payments are not allowed, inability to cover interest triggers immediate default on the entire outstanding loan.

Central bank and capital requirements framework

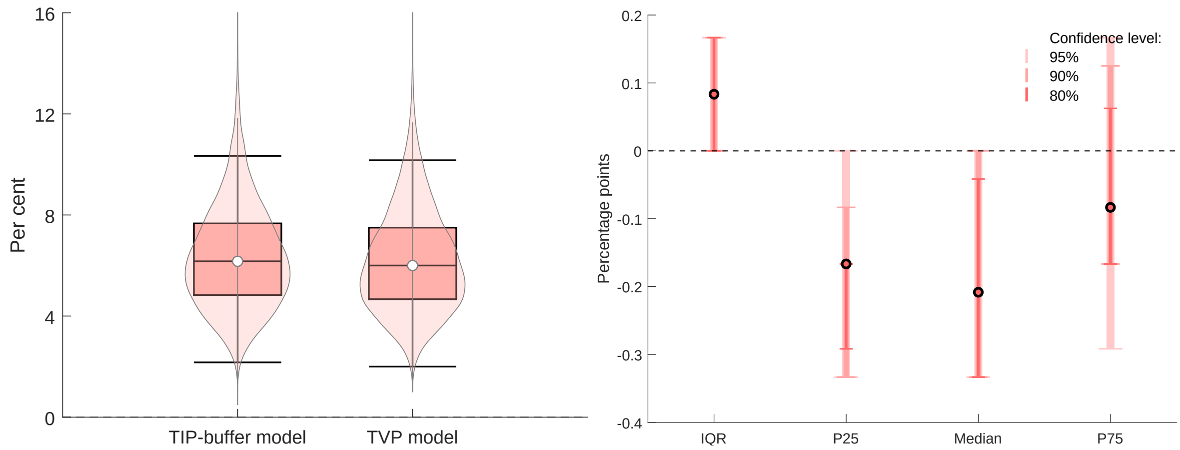
Asset classes and risk weights. Reserves are treated as risk-free and therefore carry a risk weight of zero ($rw^R = 0$). Mortgages are assigned a risk weight of 35% ($rw^H = 35\%$), reflecting the presence of collateral. Loans to firms are considered riskier and receive a risk weight of 100% ($rw^F = 100\%$). These choices follow the standardised approach to credit risk under Basel II. As a result, the total RWAs of bank b in period t are given by:

$$RWA_{b,t} = rw^R R_{b,t} + rw^H L^H_{b,t} + rw^F L^F_{b,t}.$$

B Additional results

Figure 16 illustrates the impact of buffer releases during downturns on the distribution of the unemployment rate. Relative to the TIP-buffer model, the TVP model yields a mild but statistically significant downward shift in the median and lower quartile of unemployment. Despite being economically modest, these improvements reflect the transmission mechanism embedded in the model. Releasing the buffer supports lending to firms during periods of stress, thereby reducing firm default rate, as documented in the main text. As for other macroeconomic variables, the TVP regime also delivers significant improvements in the lower tail of the distribution of house price growth, indicating that house prices fall by less during downturns when the buffer is released. However, because house prices in the current parametrisation of the model do not closely match the empirical data, given its indirect link to inflation, we treat these results as illustrative and do not report them.

Figure 16: Unemployment rate in downturns: TIP-buffer and TVP models

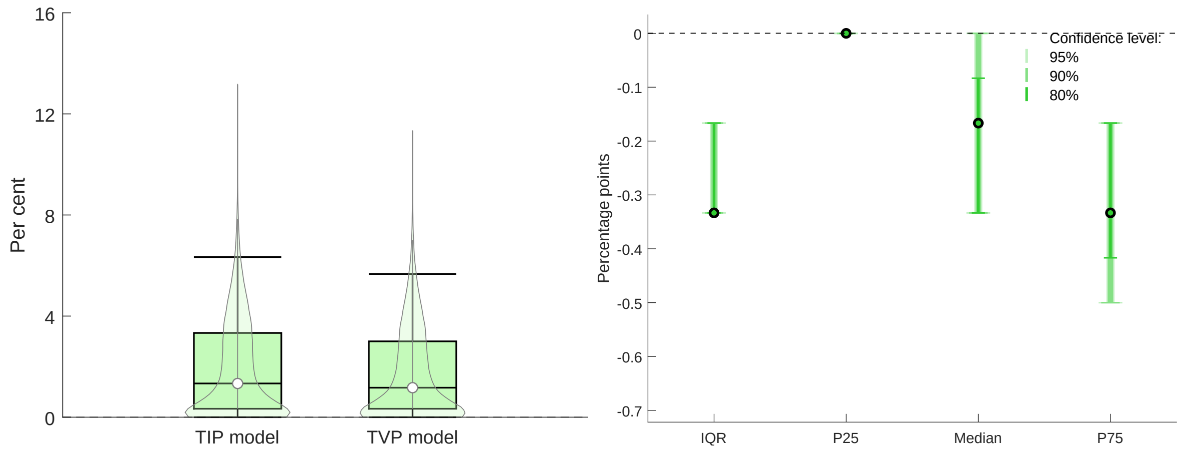


(A) Distributions (B) Confidence intervals

Note: See the notes to Figure 6 for details on the distributions and confidence intervals.

Figure 17 shows the results for the unemployment rate during upturns. Relative to the TIP model, the TVP model yields mild reductions in the median, 75th percentile, and IQR, indicating both lower and less volatile unemployment outcomes.

Figure 17: Unemployment rate in upturns: TIP and TVP models



(A) Distributions (B) Confidence intervals

Note: See the notes to Figure 6 for details on the distributions and confidence intervals.

While statistically significant, these effects are quantitatively modest, suggesting that the gradual accumulation of the buffer in the upturn does not materially impair lending to firms. In line with the broader assessment of upturn dynamics, house price growth shows limited evidence of tail costs from buffer accumulation. Differences between the TIP and TVP regimes are not statistically significant across most of the distribution, although the upper tail is somewhat higher under TVP, reflecting stronger growth in favourable states rather than increased downside risk.

C Table of parameters

Table C.1: Parameter values

Description	Parameter	Value	Source
Number of firms	F	200	Gross (2022)
Number of households	H	20000	Gross (2022)
Number of banks	B	5	Bardoscia et al. (2025)
Inflation pass-through to wages	κ	0.9	Calibration
Mortgage loan duration distr. (mean)	μ_H	5.9	Informed by Durante et al. (2025)
Mortgage loan duration distr. (var)	σ_H	0.1	Informed by Durante et al. (2025)
Marginal propensity to consume (%)	MPC	80	Calibration
Bank profit margin on loans (%)	μ	5	Gross (2022)
Fraction of homeowner households (%)	h_{frac}	75	Informed by EU data
Scale parameter of DSTI preference distr.	α	5.4	Informed by EU data
Shape parameter of DSTI preference distr.	β	8.9	Informed by EU data
Lower bound of DSTI preference distr.	L	0.05	Modeller's choice
Upper bound of DSTI preference distr.	U	0.55	Informed by Durante et al. (2025)
Consumption smoothing (%)	v	5	Calibration
Risk-weight on firm loans (%)	rw^F	100	Basel standards
Risk-weight on mortgage loans (%)	rw^H	35	Basel standards
Risk-weight on reserves (%)	rw^R	0	Basel standards
Firm loans share in credit supply (%)	λ	95	Modeller's choice
Minimum share of credit supply (%)	σ	40	Calibration

D Data used for economic validation

Table D.2: Variable definitions and data sources

Variable	Description	Source
Real GDP	Quarterly real GDP, seasonally adjusted.	EUROSTAT, FRED
Unemployment	Monthly unemployment rate.	EUROSTAT, FRED
Bank credit	Quarterly bank credit to the non-financial private sector.	BIS (Credit Statistics)

E Additional information on simulated moments

Table E.3: Simulated moments

	Mean	Std. Dev.	p25	Median	p75
Real GDP growth (%, p.a.)	4.2	4.7	1.5	4.3	6.7
Unemployment (%)	2.5	2.6	0.5	1.5	4.0
Real credit growth (%, p.a.)	5.1	14.1	-1.8	6.8	13.9
Default rate – Firms (%)	5.2	4.5	1.2	3.7	8.4
Default rate – Households (%)	3.2	3.0	0.7	2.4	4.7

Note: Std. Dev. stands for standard deviation, p25 and p75 stand for the 25th and 75th percentiles, respectively, p.a. stands for per year. Real GDP and real credit are measured as annual growth rates. The table shows the average of the different statistics across 100 independent simulations of the model, each simulating $1,850$ monthly periods with a 350 periods burn-in.

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Enrico Minnella
Bank of England, London, United Kingdom; email: enrico.minnella@bankofengland.co.uk

Ana Pereira
Bank of England, London, United Kingdom; email: ana.pereira@bankofengland.co.uk

Eugen Tereanu
European Central Bank, Frankfurt am Main, Germany; Joint Vienna Institute, Vienna, Austria; email: etereanu@jvi.org

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

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