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Summary

This paper examines the macro-financial effects of alternative adaptation strategies in response to exogenous shocks in labor productivity caused by climate change. Using a Stock-Flow-Consistent Agent-Based model calibrated to U.S. data, we analyze two main scenarios: (i) a change in the conduct of monetary policy to account for climate-related damages, and (ii) a firm-level adaptation strategy that internalizes expected climate losses. We evaluate both scenarios under the assumption of either homogeneous or heterogeneous climate shocks. Our results indicate that both strategies can mitigate the adverse effects of climate change on output and wealth distribution. However, their performance is significantly worse in the presence of heterogeneous climate shocks, which also lead to a persistent increase in firms' leverage. Moreover, while firm-level adaptation relies primarily on internal resources, monetary policy adjustments increase firms' dependence on external debt financing, underscoring the need for closer monitoring of financial stability in such circumstances.

Keywords: Integrated assessment model; Agent-based model; Financial stability; Climate change adaptation; Climate-aware monetary policy

JEL Classification: C63, E50, Q50

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Adaptation to climate-induced macrofinancial risks: top-down and bottom-up solutions

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Abstract

This paper examines the macro-financial effects of alternative adaptation strategies in response to exogenous shocks in labor productivity caused by climate change. Using a Stock-Flow-Consistent Agent-Based model calibrated to U.S. data, we analyze two main scenarios: (i) a change in the conduct of monetary policy to account for climate-related damages, and (ii) a firm-level adaptation strategy that internalizes expected climate losses. We evaluate both scenarios under the assumption of either homogeneous or heterogeneous climate shocks. Our results indicate that both strategies can mitigate the adverse effects of climate change on output and wealth distribution. However, their performance is significantly worse in the presence of heterogeneous climate shocks, which also lead to a persistent increase in firms' leverage. Moreover, while firm-level adaptation relies primarily on internal resources, monetary policy adjustments increase firms' dependence on external debt financing, underscoring the need for closer monitoring of financial stability in such circumstances.

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1 Introduction

As the impact of climate change becomes larger and more apparent, policymakers should consider proper actions to contain the economic losses and financial instability induced by extreme weather events. The IPCC reports an observed increase in climate-related damages to infrastructure, as well as the occurrence of both inland and coastal flooding, while global health and well-being are being affected by frequent heatwaves and malnutrition, as well as climate-driven displacement (Lee et al., 2023). However, while these events directly affect only a (still) small portion of households and firms, their adverse effects can propagate to the whole system through the credit market, leading to a generalized deterioration of financial conditions (Battiston et al., 2017; Dafermos et al., 2018; Lamperti et al., 2019). Therefore, while governments must address mitigation efforts to limit the direct impact of climate change, they must also develop tools to monitor and contain the ensuing instability.

With this in mind, we develop a simple Agent-Based Integrated-Assessment Model (AB-IAM) with a financial accelerator to study the propagation of climate damages in economic and financial systems, analyzing possible solutions. We employ this methodology because it allows us to study the effects of out-of-equilibrium dynamics, real and financial bottlenecks, and cognitive biases typical of structural changes such as climate change, which can amplify the direct impact of idiosyncratic shocks (Farmer et al., 2015; Balint et al., 2017). In particular, we assume that firms require credit from banks to meet short-term commitments such as labor expenses. At the same time, an exogenous climate module feeds damage into the system in the form of reduced labor productivity, thus affecting firms' profits, liquidity, and default rates. That, in turn, potentially leads to a deterioration of banks' balance sheets and a consequent credit crunch, thus amplifying the final effect of the original shock.

In this framework, we test the impact of a set of policies tackling the effects of climate change on two main fronts. First, we study the interaction between monetary policy and climate impacts through the output-gap channel, testing a policy that actively internalizes such effects. Then, we examine the application of a straightforward adaptation strategy enacted by individual firms. The aim is to assess the limits and potential of both responses (public and private) to the challenges posed by climate change, offering new insights and identifying possible risks.

This work connects to a growing body of literature analyzing the response of financial markets to climate change and climate policies (Battiston et al., 2017; Monasterolo, 2020). In particular, the risks are not limited to the direct damages to physical assets and productivity, but they extend to the potential negative consequences of poorly managed climate policy (i.e., when it is hasty or uncertain). Moreover, the financial route can amplify the adverse effects of sudden and stricter climate regulations, which need time to embed in the financial and productive system's expectations.

Conversely, when it comes to individual firms' response to climate shocks, their adaptation efforts can dampen the macroeconomic impacts (Hallegatte and Rozenberg, 2017). Indeed, if uncertainty surrounding risks is nonexistent or limited, firms affected by climate shocks may be able to adapt or recover quickly. However, when sharp damages manifest abruptly, firms may be ill-equipped to face them, as shocks would go on to propagate through the supply channels (Grover and Kahn, 2024). In reality, we may witness a combination of both, with a steady increase in temperature permanently affecting labor productivity (Adhvaryu et al., 2020) and extreme weather events disrupting production locally but more severely (Pelli et al., 2023). Following Bazzana et al. (2024), we test both scenarios by allocating climate damages homogeneously (similarly to traditional IAMs) and then heterogeneously, finding that the latter produces tougher conditions for firms trying to adapt.

Therefore, our contribution is threefold. First, we complement the AB-IAM literature by underscoring the importance of accounting for heterogeneity in climate damages when assessing the distributional and macroeconomic impacts of policy interventions. Indeed, we show that the adverse effects of heterogeneous climate shocks cannot be entirely absorbed by simple adaptation strategies. Second, our results indicate an expected rise in firms' leverage driven by the increasing frequency of extreme weather events. This finding is particularly relevant amid growing concerns over the recent global wave of debt accumulation (Kose et al., 2021; Furceri et al., 2025). Lastly, we contribute to the recent literature on climate-aware monetary policy and firms' adaptation by highlighting their differences in terms of financing sources. While a centralized (top-down) approach increases firms' dependence on debt financing, private adaptation relies more on the internal resources (i.e., the net worth) accumulated during "good" periods. Although both approaches produce similar effects on aggregate output, their implications for financial stability differ significantly.

The paper is structured as follows: Section 2 covers the relevant literature and the applied policies; Section 3 presents the model and its components; Section 4 describes the policy experiments and discusses the results; Section 5 concludes.

2 Literature

The increasing frequency and magnitude of extreme weather events worldwide (IPCC, 2023) has raised concerns among central banks and policymakers, whose attention is no longer limited to managing economic and financial fluctuations alone. The propagation of climate-induced damages throughout the economy introduces new challenges for monetary and financial policy, which must adapt to the new context, thus explaining the growing literature on this topic (Campiglio, 2016; Battiston et al., 2017; Dafermos et al., 2018; Monasterolo, 2020; Lamperti et al., 2019, 2021).

Among these contributions, Agent-Based Integrated Assessment Models (AB-IAMs) have emerged as a promising framework for analyzing climate-induced financial instability and its interaction with macro-stabilizing policies (Moss et al., 2001; Lamperti et al., 2018b). This approach (see, for instance, Gerst et al., 2013; Lamperti et al., 2018a; Giarola et al., 2022; Bazzana et al., 2024) entails developing a simulated economy populated by multiple agents belonging to different classes (e.g., households, firms, and banks). By explicitly modeling market interactions and introducing a climate module, AB-IAMs can replicate some of the emergent dynamics of economic and financial systems (Axtell and Farmer, 2022), including the second-order impact of climate-induced damages.

Several benefits derive from this framework. Firstly, it can integrate economic models with credit and money markets, thus capturing the effects of the financial accelerator (Delli Gatti et al., 2005, 2010). This feature allows replicating the endogenous polarization in the credit sector leading to the rise of crises and recessions. As a result, climate shocks can affect solvency, and financial instability amplifies their damages. Secondly, ABMs allow practitioners to observe the evolution of agents' characteristics at the micro level (e.g., the net worth distribution over time). Therefore, the distributional implications of shocks and policies are easily identifiable.

Concerning which policies ought to be reevaluated to test their resilience to the new climate conditions, monetary policy is a crucial tool requiring a more climate-aware approach to face the new environment. A rising body of literature (Economides and Xepapadeas, 2018; Schoenmaker, 2021; Batten et al., 2020; Dafermos et al., 2018; Campiglio, 2016) points out the potential for central banks to broaden their scope to climate policy, especially considering the direct impact of climate change on output and, indirectly, via fiscal policy, on inflation. Depending on the ultimate goal of a central bank, may it be price stability, improving net exports, or controlling unemployment, conjunctively tackling climate issues might have unintended consequences. Indeed, it may limit the effectiveness of traditional policy tools, making their short-term objectives more difficult to achieve. Moreover, climate mitigation and adaptation traditionally belongs to the domain of fiscal policy since taxation is the way economic theory usually deals with these externalities, and it may indirectly impact monetary policy in a non-trivial way.

According to Economides and Xepapadeas (2018), policymakers should interpret climate damages as a series of (real) autocorrelated negative supply shocks. Those shocks may hamper productivity, thus fueling inflation and increasing interest rates (possibly decreasing fossil fuel consumption at the same time). Eventually, they argue for adjusting monetary tools to account for climate effects when applied in conjunction with carbon (or energy) taxation. Still, their model addresses a global-scale effect with local (regional at most) policy tools.

Concerning the legitimacy of "green" (or simply climate-aware) monetary policy, Schoenmaker (2021) highlights the market bias towards carbon and capital-intensive firms as the source of their over-representation in market indices (Matikainen et al., 2017). This undermines the climate neutrality of central banks. In particular, they claim that in the case of the European Central Bank (ECB), market neutrality is plainly in contrast with the EU's Greenhouse Gas (GHG) emissions reduction objectives. Nevertheless, the EU Treaties' definition of economic policies is broad enough to allow the ECB to include climate objectives into its mandate, in a way that does not hinder the implementation of monetary policy. Batten et al. (2020) identify the main channels through which climate change can affect the goals of monetary policy. Physical risk negatively impacts the balance sheets of banks, firms, insurers, and households. On the one hand, insurance and reinsurance may be an effective tool to dampen these financial downturns. On the other hand, monetary policy may account for the weight of climate shocks in the main macroeconomic indicators. For instance, climate shocks may widen the output gap by reducing potential output, effectively leading to overly-accommodating policy rates.

Finally, as opposed to monetary policy top-down perspectives, also firm-level (i.e., bottom-up) adaptation has the potential to reduce climate impacts. As emphasized by Grover and Kahn (2024), when firms have perfect foresight concerning climate shocks, they can take countermeasures to offset the negative impacts of damages on their own productivity. This may happen as firms relocate either physically or in the market towards less exposed areas (Khanna et al., 2025), sectors (Colmer, 2021), or input allocations (Zhang et al., 2018). On the other hand, firm-specific factors (such as size) may determine the success of a firm's adaptation and recovery efforts. Moreover, the way climate shocks affect firms has deep consequences on their chances of survival. Only some climate impacts manifest slowly over time: for example, the increase in frequency and intensity of heatwaves negatively affects productivity in the short term (Zhang et al., 2018; Cachon et al., 2012). At the same time, localized extreme-weather events may substantially curb firms' output and sales (Pelli et al., 2023). Lastly, firms face uncertainty regarding the timing and magnitude of climate risks, and climate uncertainty alone can determine a significant erosion of aggregate output (Jia et al., 2022).

3 Model

In the simulated economy, a population of firms produces a homogeneous good using capital and labor as inputs. While they can accumulate production into new capital (but not vice versa), firms must employ an external workforce to finalize output. Further, since they must pay wages in advance, they resort to bank credit whenever their financial resources are insufficient. Lastly, they set prices and desired quantities through an endogenous learning mechanism that considers excess demand/supply and the observed behavior of the most profitable competitors (Ciola et al., 2023; Turco et al., 2023).

The credit sector comprises a set of heterogeneous banks connected to firms through a decentralized matching protocol. When a firm requires additional financial resources, a matched bank can extend an open-ended credit line that the borrower repays as soon as possible. The interest rate on the loan rises with the firm's leverage, reflecting the increased risk of default. In the event of liquidity shortage, the firm can try to extend the existing credit line from the bank or recapitalize through the entrepreneur's money. If neither option is viable, the firm goes bankrupt.

To keep the model as simple as possible, we introduce households as an aggregate entity, implementing a stylized, frictionless labor market with infinite supply and a quasi-replicator dynamic for the consumption goods market. The latter allocates aggregate demand to individual firms reflecting their past sales and current prices. A central bank controls inflation by setting interest rates through an inertial Taylor rule, and the government bails out banks from bankruptcy to contain the downturns of business and financial cycles.

In our simplified framework, the link between the environment and the economy is one-way.[1] We rely on exogenous projections of global CO_2 emission for the twenty-first century and a temperature-denominated damage function to model the impact of climate change as a reduction in labor productivity.

Lastly, since our analysis focuses on the economic and financial effects of climate shocks, we need a modeling framework capable of representing the real and monetary flows characterizing modern economies. Accordingly, the model is Stock-Flow-Consistent (SFC), meaning that: (i) agents and sectors are limited by budget and financial constraints; (ii) sectors are intertwined by precise relations; (iii) no resources can vanish or originate from nothing; (iv) the laws of motion of stock variables at the beginning of each period determine the evolution of the system (Zezza, 2004; Dos Santos, 2005; Lavoie, 2008). By employing these simple rules, we reduce the effects that random and arbitrarily chosen variables can have on simulations. Figure 1 shows a flow chart of the model, while we report the complete matrices with the aggregate balance sheets and transaction flows in Tables A.1 and A.2 of the Appendix A.

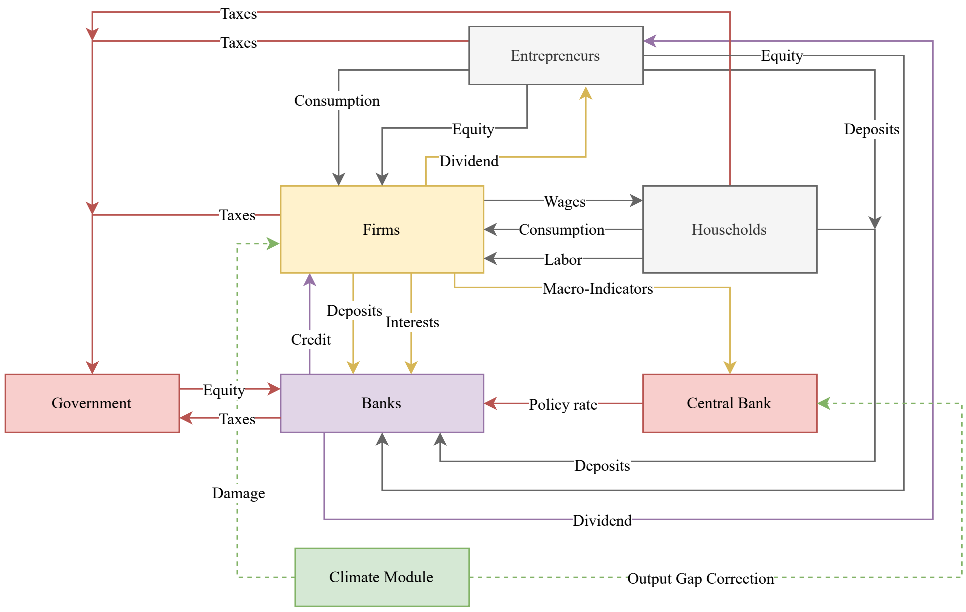


Figure 1: Flow chart of the model

Note: Colors identify outflows: yellow from firms, purple from banks, gray from entrepreneurs and the representative household. Red flows and boxes indicate policymakers and their decisions.

[1]In other words, we exclude mitigation efforts from the scope of this work. Under this assumption, we exclude any national political will or capacity to mitigate climate change or to affect global climate dynamics. Nevertheless, it allows us to isolate the impact of the policies we test.

3.1 Sequence of the events

At each time step, the economy evolves through a recursive and iterative process in which agents interact as follows (Delli Gatti et al., 2018):

- Given the stock of capital, debt, and liquidity from the previous period, firms hire workers, pay wages, and carry out production.
- Goods market opens: consumers select firms based on their *fitness* — defined by past sales and current prices — and trade. All the excess production (demand) accumulates in the form of additional capital (involuntary savings).
- Firms compute profits, pay taxes, and distribute dividends. Those with negative net worth or experiencing financial distress due to liquidity shortages fail.
- Firms set future production targets, input demand, and prices by imitating more successful competitors. In the absence of a viable competitor, firms revise their strategy based on their own excess supply/demand and the average market price.
- The central bank adjusts the risk-free interest rate following an inertial Taylor rule.
- Credit market opens: firms determine their credit demand and select banks according to their *fitness*, defined by the potential credit supply and the current interest rate. Loans are issued, and corresponding interest rates are established.
- Banks compute profits/losses, pay taxes, and distribute dividends.
- Banks with negative net worth declare bankruptcy. In such cases, the government intervenes to cover the losses acting as a lender of last resort. The entrepreneurs, who collectively own the banks, provide the necessary resources to meet capital and reserve requirements.

3.2 Firms

Production

In every period $t = 1, ..., T$, firms $f = 1, ..., \mathcal{N}^F$ (each owned by an entrepreneur, $e = f$) employ capital $K_{f,t}$ and labor $N_{f,t}$ to produce a homogeneous good[2] $Y_{f,t}$ within a Leontief production function:[3]

$$Y_{f,t} = \min\left[\theta_1 K_{f,t}, (1 - \psi_{f,t})\theta_2 N_{f,t}\right], \tag{1}$$

where θ_1 and θ_2 are input productivities, and $\psi_{f,t}$ is the percentage reduction in labor efficiency due to climate shocks.

[2] The homogeneous good can be either be used for final consumption by households or capital accumulation by firms.

[3] This functional form approximates a setting characterized by low substitutability between labor and capital (as supported by empirical evidence, see Gechert et al., 2022) and allows stressing the impact of both endogenous liquidity crises and exogenous shocks to productivity (e.g., climate damages).

While firms must set capital $K_{f,t}$ in advance, they are free to hire/fire any quantity of work in the short term. Nevertheless, they must pay wages in advance, and the actual amount of labor $N_{f,t}$ depends on firms' demand $N^d_{f,t}$ (see the paragraph *Input demand* later in this section) and the available financial resources (i.e., their deposits) $Dep_{f,t}$, namely:

$$N_{f,t} = \min\left(\frac{Dep_{f,t}}{w_t}, N^d_{f,t}\right), \tag{2}$$

where w_t is the aggregate wage, assumed to be unitary and constant over time ($w_t = 1$ for $t = 1, \dots, T$).

Product demand and supply

Total consumption budget H_t is given by the sum of individual entrepreneurs' and aggregate workforce's consumption budgets ($H_{e,t}$ and $H_{w,t}$, respectively, see Section 3.4):

$$H_t = H_{w,t} + \sum_{e=1}^{\mathcal{N}^F} H_{e,t}. \tag{3}$$

Firms' demand (i.e., the individual consumption budget, $H_{f,t}$) evolves following a quasi-replicator dynamic that distributes the aggregate expenditure H_t among producers according to their competitiveness (see Fontanelli, 2024, for a review). In particular, each firm faces the nominal demand:

$$H_{f,t} = \left[\theta_D \frac{H_{f,t-1}}{H_{t-1}} + (1-\theta_D)\pi_{f,t}\right] H_t, \tag{4}$$

where the allocated budget depends on the firm's share of past demand ($H_{f,t-1}/H_{t-1}$), with the weight θ_D capturing the degree of persistence, and on the probability:

$$\pi_{f,t} = \frac{\eta_{f,t}^{\beta_D}}{\sum_{f=1}^{\mathcal{N}^F} \eta_{f,t}^{\beta_D}}, \tag{5}$$

which is a function of the firm's *fitness*:

$$\eta_{f,t} = \omega_D \frac{C_{f,t-1} - \min_f(C_{f,t-1})}{\max_f(C_{f,t-1}) - \min_f(C_{f,t-1})} + (1-\omega_D)\frac{\max_f(p_{f,t}) - p_{f,t}}{\max_f(p_{f,t}) - \min_f(p_{f,t})}. \tag{6}$$

The latter measures a firm's attractiveness, with the parameter β_D capturing the level of competition in the market (see Delli Gatti et al., 2010; Riccetti et al., 2013; Lenzu and Tedeschi, 2012; Ciola et al., 2022, for related applications). The fitness increases with past sales $C_{f,t-1}$ (see 10) and decreases with the price $p_{f,t}$, both of which are normalized between zero and one. The higher (lower) a firm's past market share (current price), the greater its ability to attract new consumers. The parameter ω_D weighs this aspect in the fitness function.

Therefore, each firm faces the demand:

$$C^d_{f,t} = \frac{H_{f,t}}{p_{f,t}}, \tag{7}$$

while the final good supply is determined as the gross output net of investments:

$$C^s_{f,t} = Y_{f,t} - I_{f,t}, \tag{8}$$

where investments $I_{f,t}$ are set as the minimum between production and net capital demand:

$$I_{f,t} = \max\left\{0, \min\left[K^d_{f,t+1} - (1-\delta_F)K_{f,t}, Y_{f,t}\right]\right\}, \tag{9}$$

with $K^d_{f,t+1}$ being the demanded quantity of capital (see the paragraph *Input demand* later in this section), and δ_F its depreciation rate.

Lastly, actual sales are given by the minimum between a firm's supply and the demand it faces, namely:

$$C_{f,t} = \min\left(C^d_{f,t}, C^s_{f,t}\right). \tag{10}$$

The unsold quantity $(C^s_{f,t} - C_{f,t})$ adds to firm's existing capital, while nominal excess demand $(\sum_{f=1}^{\mathcal{N}^F} \max\left[0, H_{f,t} - p_{f,t}C_{f,t}\right])$ is distributed across consumers (i.e., the aggregate workforce and individual entrepreneurs) proportionally to their budgets in the form of unwanted savings.

Price and production goal setting

Selling prices $p_{f,t}$ and future production targets $Y^*_{f,t}$ are the result of a layered decision process in which firms mirror the strategy of most profitable competitors.[4] After observing a random competitor $\mathcal{F}$, if the latter displays higher profits (i.e., if $\Pi_{\mathcal{F},t} > \Pi_{f,t}$), each firm f moves towards its strategy by imitation:

$$p_{f,t+1} = \left[1 + z \cdot \mu_F \cdot \operatorname{sgn}\left(p_{\mathcal{F},t} - p_{f,t}\right)\right] \cdot p_{f,t}, \tag{11}$$

$$Y^*_{f,t+1} = \left[1 + z \cdot \rho_F \cdot \operatorname{sgn}\left(Y^*_{\mathcal{F},t} - Y^*_{f,t}\right)\right] \cdot Y^*_{f,t}, \tag{12}$$

where $\operatorname{sgn}(\cdot)$ is the sign function, and $z \sim U(0,1)$ is a random sample from a standard uniform distribution. The parameters μ_F and ρ_F determine the size of the increase (or reduction) in prices and production goals, i.e., the speed of the adjustment mechanism.

Conversely, if the competitor is not worth imitating (i.e., if $\Pi_{\mathcal{F},t} \leq \Pi_{f,t}$), the firm adapts its strategy according to observable metrics (Assenza et al., 2015; Giri et al.,

[4] This price-quantity setting mechanism shares similarities with those used in other macro-ABMs (e.g., Assenza et al., 2015; Giri et al., 2019) where excess demand and price competition govern the process. Moreover, as in Ciola et al. (2022, 2023), we integrate the process with strategic complementarities among firms (Pitschner, 2020).

2019). Excess demand or supply ($C^d_{f,t} \lesseqgtr C^s_{f,t}$) and past prices relative to the average level ($p_{f,t} \lesseqgtr \bar{p}_t$) guide the pricing decision, namely:

$$p_{f,t+1} = \begin{cases} (1 + z \cdot \mu_F) \cdot p_{f,t} & \text{if } p_{f,t} < \bar{p}_t \text{ and } C^d_{f,t} > C^s_{f,t}, \\ (1 - z \cdot \mu_F) \cdot p_{f,t} & \text{if } p_{f,t} > \bar{p}_t \text{ and } C^d_{f,t} < C^s_{f,t}. \end{cases} \tag{13}$$

A firm facing an excess of demand while having an overly competitive price increases it. Conversely, if a firm witnesses a decline in demand and its price is above the average, it revises it downwards to become more competitive.

The decision regarding the production goal follows a similar pattern:

$$Y^*_{f,t+1} = \begin{cases} (1 + z \cdot \rho_F) \cdot Y^*_{f,t} & \text{if } p_{f,t} > \bar{p}_t \text{ and } C^d_{f,t} > C^s_{f,t}, \\ (1 - z \cdot \rho_F) \cdot Y^*_{f,t} & \text{if } p_{f,t} < \bar{p}_t \text{ and } C^d_{f,t} < C^s_{f,t}. \end{cases} \tag{14}$$

The production goal increases when the firm observes an excess of demand and its price is above the market average. On the contrary, it decreases if the firm already offers a competitive price but is still in oversupply.

Input demand

Once the desired production has been set, firms compute their input demand. By rearranging (1), the required capital and labor are:

$$K^d_{f,t+1} = \frac{Y^*_{f,t+1}}{\theta_1} \quad \text{and} \quad N^d_{f,t+1} = \frac{Y^*_{f,t+1}}{\theta_2}. \tag{15}$$

Since climate damages affect labor efficiency, firms may opt to internalize the projected decline in productivity by employing a moving average of past experienced damages $\bar{\psi}_{f,t}$, namely:[5]

$$N^d_{f,t+1} = \frac{Y^*_{f,t+1}}{\theta_2 \left(1 - \bar{\psi}_{f,t}\right)}. \tag{16}$$

Profits, liquidity, and defaults

The gross profit of each firm ($\Pi^{gross}_{f,t}$) is equal to nominal production net of labor costs, capital depreciation, and financial expenses:

$$\Pi^{gross}_{f,t} = p_{f,t} Y_{f,t} - w_t N_{f,t} - \delta_F K^N_{f,t} - i_{f,t} L_{f,t}, \tag{17}$$

where $i_{f,t}$ is the interest rate applied to outstanding loans $L_{f,t}$, and the nominal capital $K^N_{f,t}$ evolves according to the law of motion:[6]

$$K^N_{f,t+1} = p_{f,t} I_{f,t} + p_{f,t} \left(Y_{f,t} - C_{f,t}\right) + (1 - \delta_F) K^N_{f,t}. \tag{18}$$

[5] In other words, when we test for firms' adaptation, we assume they revise labor productivity downwards in anticipation of climate shocks.

[6] The term $p_{f,t} \left(Y_{f,t} - C_{f,t}\right)$ indicates the accumulation of unsold goods in the form of additional capital (see the previous paragraph *Product demand and supply* in this section).

Similarly, the firm's liquidity varies according to its short-term commitments, such as labor compensation, taxes, and revenues generated by sales $C_{f,t}$. Accordingly, deposits increase with nominal revenues ($p_{f,t}C_{f,t}$) and decrease with labor expenses ($w_t N_{f,t}$) and taxes ($T_{f,t}$), following the law of motion:

$$Dep_{f,t+1} = Dep_{f,t} + p_{f,t}C_{f,t} - w_t N_{f,t} - T_{f,t}. \tag{19}$$

Taxes $T_{f,t}$ depend on the rate set by the government (τ_t) and the firm's actual liquidity, namely:

$$T_{f,t} = \min\left[\max\left(0, \tau_t \Pi^{gross}_{f,t}\right), Dep_{f,t} + p_{f,t}C_{f,t} - w_t N_{f,t}\right], \tag{20}$$

and are subtracted from gross profits, leaving the net value:

$$\Pi^{net}_{f,t} = \Pi^{gross}_{f,t} - T_{f,t}, \tag{21}$$

which enters the firm's net worth as follows:

$$A_{f,t+1} = A_{f,t} + \Pi^{net}_{f,t}. \tag{22}$$

Firms can operate only as long as their net worth is positive, and excessive losses may undermine their solvability. When the net worth of a firm turns negative (i.e., $A_{f,t+1} < 0$), it defaults and ceases to exist. In its place, the entrepreneur founds a new company, financing it with its own deposits.[7] Meanwhile, the connected bank tries to limit losses by selling the capital of the defaulted firm to the newly established one. The recovered value ($K^{rec}_{f,t+1}$) depends on the book value of capital ($K^{N}_{f,t+1}$) and the available liquidity in the new firm ($Dep_{f,t+1}$):

$$K^{rec}_{f,t+1} = \min\left(K^{N}_{f,t+1}, Dep_{f,t+1}\right), \tag{23}$$

and the difference with outstanding debt ($L_{f,t}$) determines the size of debt shortfall ($S_{f,t}$):

$$S_{f,t} = L_{f,t} - K^{rec}_{f,t+1}. \tag{24}$$

In some cases, firms are not on the verge of bankruptcy but may still experience financial distress. That happens when the available liquidity is not sufficient to pay back interest on outstanding loans (i.e., $Dep_{f,t+1} - i_{f,t}L_{f,t} < 0$). In this case, recapitalization can occur through the banking system, with an extension of the existing credit line, and/or through the entrepreneur, with a liquidity injection. The feasibility condition for recapitalization is:

$$Dep_{f,t+1} - i_{f,t}L_{f,t} + \Delta L^{L}_{b,t+1} + Dep_{e,t} \geq 0, \tag{25}$$

where the additional debt $\Delta L^{L}_{b,t+1}$ must respect all the legal requirements (see Section 3.3). If that is not the case, the firm defaults.

[7]The entrepreneur does not provide all its liquidity, but only the amount necessary to repurchase capital and finance labor costs in the subsequent period.

Lastly, if a company is financially sound, it pays interest to the bank ($i_{f,t}L_{f,t}$) and distribute dividends ($Div_{f,t}$) to the entrepreneur, computed as a fixed proportion η_F of its net worth. In any case, the firm ensures that planned labor costs are met with current financial resources:

$$Div_{f,t} = \max\left[0, \min\left(\eta_F A_{f,t+1}, Dep_{f,t+1} - w_{t+1}N^d_{f,t+1}\right)\right]. \tag{26}$$

The net worth and deposits of the firm and the entrepreneur are updated accordingly.

3.3 Banks

When internal financial resources are insufficient to carry out production targets, firms can resort to an external source of financing by entering the credit market. After defining their demand for credit, they select banks based on their *fitness*, i.e., depending on the potential credit supply and the current interest rate. Banks then update their net worth by considering the interest received on past debts, non-performing loans, and new credit issuances, recapitalizing if necessary.

Credit demand and supply

At the end of every period, firms compute their financing gap, i.e., the difference between the available deposits ($Dep_{f,t+1}$), upfront labor expenses ($w_{t+1}N^d_{f,t+1}$), and liquidity shortage ($\Delta L^L_{b,t+1}$, see 25) to define their additional demand for credit:[8]

$$\Delta L^d_{f,t+1} = \max\left(-L_{f,t}, w_{t+1}N^d_{f,t+1} + \Delta L^L_{b,t+1} - Dep_{f,t+1}\right). \tag{27}$$

Banks ($b = 1, ..., \mathcal{N}^B$) must respect capital and reserve requirements when lending. Given the net worth ($A_{b,t}$) and total debt ($L_{b,t}$) at the beginning of the period, along with current deposits ($Dep_{b,t+1}$),[9] they can supply the additional amount of credit:

$$\Delta L^s_{b,t+1} = \max\left[0, \min\left(\Delta L^C_{b,t+1}, \Delta L^R_{b,t+1}\right)\right], \tag{28}$$

where the first term:

$$\Delta L^C_{b,t+1} = \frac{A_{b,t}}{\nu_{CB}} - L_{b,t}, \tag{29}$$

derives from capital regulation, with ν_{CB} being the constant capital requirement, and:

$$\Delta L^R_{b,t+1} = A_{b,t} + Dep_{b,t+1}\left(1 - \gamma_{CB}\right) - L_{b,t}, \tag{30}$$

are the reserve requirements, with γ_{CB} being the total reserve ratio.

[8] If the additional demand $\Delta L^d_{f,t+1}$ is below zero, the firm closes (part of) its credit line.

[9] We assume that firms (and related entrepreneurs) deposit in the same bank from which they (used to) borrow. Since single households are not modeled explicitly, we split their aggregated deposits among banks according to the share of the workforce employed by firms.

Interest rates and partner selection

We assume that each firm can borrow from only one bank at a time due to information imperfections, thus implying a star topology financial network in which many firms are connected to a single bank (see, for example, Grilli et al., 2014; Ciola et al., 2022). We model the matching protocol of the credit market as a process in which firms search for the bank offering the best contractual conditions (i.e., the bank with the highest *fitness*), determined by the interest rate $i^*_{b,t+1}$ and the potential credit supply $L^*_{b,t+1}$.

The interest rate depends on the joint characteristics of the firm and the bank, namely:

$$i^*_{b,t+1} = i^{taylor}_{t+1} + \delta_B + \alpha_B \ell_{f,t+1} - \zeta_B n_{b,t+1}, \tag{31}$$

where i^{taylor}_{t+1} is the policy rate set by the central bank. The parameter δ_B pertains to systemic risk pricing, while α_B and ζ_B measure firm- and bank-specific risk components. On the one hand, the bank-specific risk decreases with the normalized market share of loans $n_{b,t+1} = (L_{b,t+1}/\sum_b L_{b,t+1})/(1/\mathcal{N}^B)$, as a measure of portfolio diversification. On the other hand, the firm-specific risk rises with the expected leverage $\ell_{f,t+1} = L_{f,t+1}/(A_{f,t+1} + L_{f,t+1})$, which is used as a proxy for future solvability.

Conversely, $L^*_{b,t+1}$ represents the average amount of credit that a bank can potentially lend to its borrowers, which is defined as follows:

$$L^*_{b,t+1} = \frac{L_{b,t} + \Delta L^s_{b,t+1}}{|\mathcal{S}^L_{b,t}|}, \tag{32}$$

where $|\mathcal{S}^L_{b,t}|$ is the number of firms connected to the bank in the previous period. In other words, this value serves as a proxy for a bank's potential credit supply to a new borrower who is considering it.

Similarly to consumers, firms search for the bank with the highest *fitness*, i.e., depending on the interest rate $i^*_{b,t+1}$ and the potential credit supply $L^*_{b,t+1}$. In every period, each firm looks for a new lender with probability θ_B and observes a specific bank b with a chance equal to:

$$\pi_{b,t} = \frac{\eta_{b,t}^{\beta_B}}{\sum_{b=1}^{\mathcal{N}^B} \eta_{b,t}^{\beta_B}}, \tag{33}$$

which is a function of its *fitness*:

$$\eta_{b,t} = \omega_B \frac{L^*_{b,t+1} - \min_b(L^*_{b,t+1})}{\max_b(L^*_{b,t+1}) - \min_b(L^*_{b,t+1})} + (1-\omega_B)\frac{\max_b(i^*_{b,t+1}) - i^*_{b,t+1}}{\max_b(i^*_{b,t+1}) - \min_b(i^*_{b,t+1})}. \tag{34}$$

As in the consumption goods market, the parameter β_B measures the degree of competition in the market, while ω_B determines the price-quantity tradeoff.

The firm switches to the new bank if the latter can provide sufficient resources to cover its outstanding loan (i.e., if $L_{f,t} \leq \Delta L^s_{b,t+1}$). In that case, existing financial positions are updated (i.e., the firm's deposits and loan, as well as the credit supply of the new and the old bank), and the size of the new credit line is set equal to:

$$L_{f,t+1} = \min\left(\Delta L^s_{b,t+1}, L_{f,t} + \Delta L^d_{f,t+1}\right). \tag{35}$$

Conversely, if the new bank cannot meet the firm's financial needs, the latter remains with its old partner and update its credit line as follows:

$$L_{f,t+1} = \min\left(\Delta L^s_{b,t+1}, \Delta L^d_{f,t+1}\right) + L_{f,t}. \tag{36}$$

Profits and default mechanism

The net profit of each bank b depends on the interest received on its portfolio of loans ($\sum_{f\in\mathcal{S}^L_{b,t}} i_{f,t}L_{f,t}$) net of marginal operating costs (c_B), losses on non-performing debt ($S_{f,t}$), and taxes ($T_{b,t}$):

$$\Pi^{net}_{b,t} = \sum_{f\in\mathcal{S}^L_{b,t}} (i_{f,t} - c_B)\, L_{f,t} - \sum_{f\in\mathcal{S}^D_{b,t}} (S_{f,t} + i_{f,t}L_{f,t}) - T_{b,t}, \tag{37}$$

where $\mathcal{S}^L_{b,t}$ is the set of firms borrowing from the bank in the previous period, and $\mathcal{S}^D_{b,t} \subseteq \mathcal{S}^L_{b,t}$ represents those which went bankrupt. Taxes $T_{b,t} = \max(0, \tau_t\Pi^{gross}_{b,t})$ are a fraction τ_t of the bank's gross profit $\Pi^{gross}_{b,t}$, and the law of motion of the net worth is given by:

$$A_{b,t+1} = A_{b,t} + \Pi^{net}_{b,t}. \tag{38}$$

Similarly to firms, banks default if their net worth turns negative (i.e., if $A_{b,t+1} < 0$). However, the burden of the bankruptcy falls entirely on the government, which covers the losses through additional public expenditure. Moreover, each bank's net worth must meet capital and reserve requirements:

$$A^{req}_{b,t+1} = \max\left[\nu_{CB}L_{b,t+1}, L_{b,t+1} - (1-\gamma_{CB})\, Dep_{b,t+1}\right], \tag{39}$$

where ν_{CB} is the capital requirement, γ_{CB} the reserve ratio, $L_{b,t+1}$ and $Dep_{b,t+1}$ are the bank's loans and deposits after the credit market closes (i.e., after new debt creation and closure).

If a bank fails to meet capital and reserve requirements, it calculates the amount needed for recapitalization:

$$\Delta A_{b,t+1} = \max\left(0, A^{req}_{b,t+1} - A_{b,t+1}\right), \tag{40}$$

and resorts to entrepreneurs' deposits (who own it collegially) to recapitalize itself. The entrepreneurs who participate in the equity increase raise their ownership shares accordingly (see Section 3.4). When this is not feasible (due to limitations in entrepreneurs' resources), the government acts as a lender of last resort. Therefore, the public expenditure G_t is expressed as:

$$G_t = -\sum_{b\in\mathcal{S}^D_t} A_{b,t+1} + \sum_{b\in\mathcal{S}^R_t} \Delta A_{b,t+1}, \tag{41}$$

where $\mathcal{S}^D_t$ and $\mathcal{S}^R_t$ are the set of banks in default and in need of recapitalization, respectively.

On the contrary, a healthy bank pays a dividend $Div_{b,t}$ to the entrepreneurs who own it, distributed according to their equity shares:

$$Div_{b,t} = \max\left[0, \min\left(\eta_B A_{b,t+1}, A_{b,t+1} - A^{req}_{b,t+1}\right)\right], \tag{42}$$

where η_B is a fixed portion of the bank's equity. The net worth and deposits of banks and entrepreneurs are then updated accordingly.

3.4 Consumers

Entrepreneurs

Each entrepreneur privately owns a firm ($e = f = 1, ..., \mathcal{N}^F$), invests in banks' shares, and participates in aggregate consumption through the individual budget:

$$H_{e,t} = \min\left(\iota_E NW_{e,t}, Dep_{e,t}\right), \tag{43}$$

which depends on its short-term availabilities (i.e., the deposits $Dep_{e,t}$), and a constant parameter ι_E, representing the propensity to consume out of net worth $NW_{e,t}$.

In each period, entrepreneurs' deposits ($Dep_{e,t}$) and net worth ($NW_{e,t}$) vary according to specific occurrences: i) both decrease with consumption; ii) dividend payments and recapitalizations modify their composition; iii) defaults directly affect only the net worth. The latter is defined as follows:

$$NW_{e,t} = Dep_{e,t} + A_{f,t} + \sum_{b=1}^{\mathcal{N}^B} A_{e,b,t}, \tag{44}$$

where $A_{f,t}$ is the equity of the related firm f, and $A_{e,b,t}$ are the market shares of bank b in possession of entrepreneur e at the beginning of time t.

Indeed, while firms are privately owned, banks' shares are freely available on the market. Entrepreneurs purchase them during recapitalizations and resell them through dividend payments (i.e., buybacks). The distribution of banks' shares changes over time depending on entrepreneurs' liquidity during recapitalizations, namely:

$$\Delta A_{e,b,t} = \frac{Dep_{e,t+1}}{\sum_{e=1}^{\mathcal{N}^F} Dep_{e,t+1}} \Delta A_{b,t+1}, \tag{45}$$

where $\Delta A_{b,t+1}$ is defined as in (40). In other words, the higher the deposits, the higher the investment in banks requiring additional capital. Conversely, dividend payments and defaults affect market shares proportionally, i.e., without modifying the ownership structure.

Households

In this model, households are an aggregate entity that supplies work ($N_{f,t}$) to firms in exchange for a salary (w_t). They collectively hold deposits ($Dep_{w,t}$) and entirely consume all the available resources (i.e., they behave as hand-to-mouth consumers like in Lamperti et al., 2018a) by setting the aggregate budget:

$$H_{w,t} = \sum_{f=1}^{\mathcal{N}^F} (1 - \tau_t)\, w_t N_{f,t} + c_B L_t + Dep_{w,t}, \tag{46}$$

where $c_B L_t = \sum_{b=1}^{\mathcal{N}^B} c_B L_{b,t}$ are the operating expenses (i.e., the labor cost) sustained by the banking sector, and τ_t is the tax rate on gross labor income $\sum_{f=1}^{\mathcal{N}^F} w_t N_{f,t}$.

Therefore, households' deposits (and net worth) evolve according to the rule:

$$NW_{w,t+1} = Dep_{w,t+1} = Dep_{w,t} + \sum_{f=1}^{\mathcal{N}^F} (1 - \tau_t)\, w_t N_{f,t} + c_B L_t - \bar{p}_t C_{w,t}. \tag{47}$$

As for the entrepreneurs, the consumption budget may not be entirely spent due to a lack of supply (i.e., $\bar{p}_t C_{w,t} \leq H_{w,t}$).

3.5 The central bank

The central bank enforces a "dual mandate" policy that aims to contain both inflation and the output gap. The policy rate is set according to an inertial Taylor rule (Curdia and Woodford, 2010):

$$i_t^{taylor} = \max\left[0, \rho_{CB} i_{t-1}^{taylor} + (1 - \rho_{CB})\left(r^* + \pi^* + \pi_{CB}\left(\pi_t - \pi^*\right) + y_{CB}\left(y_t - y_t^*\right)\right)\right], \tag{48}$$

where ρ_{CB} is a partial adjustment factor capturing the persistence of monetary policy, π_t and π^* represent current and target inflation rate (i.e., the growth rate of the average price index, $\bar{p}_t$), while y_t^* is the output gap target and y_t its realized value at time t. Finally, r^* is the natural interest rate, while π_{CB} and y_{CB} are the relative weights of inflation and output gap, respectively, determining their influence on the policy rate.

The output gap y_t is defined as the percentage deviation of the aggregate output $Y_t = \sum_{f=1}^{\mathcal{N}^F} Y_{f,t}$ from its potential level $Y_t^* = \sum_{f=1}^{\mathcal{N}^F} Y_{f,t}^*$, the latter computed as the sum of production goals across all firms:

$$y_t = \frac{Y_t}{Y_t^*} - 1. \tag{49}$$

In this setting, the output gap is always negative by construction (i.e., $y_t \leq 0$). Accordingly, we assume that the central bank sets the output gap target y_t^* based on the historical average:

$$y_t^* = \frac{1}{t} \sum_{s=1}^{t} y_s. \tag{50}$$

In this way, it can evaluate short-term fluctuations while accounting for the long-term trend.

Lastly, the role of the central bank is limited to these identities in the *Baseline* scenario, i.e., focusing on controlling inflation and managing endogenous financial downturns. However, after introducing climate damages, the central bank can adapt its policy by internalizing the exogenous decline in labor productivity due to those shocks. Indeed, climate damage tends to overinflate the output gap by reducing the aggregate output Y_t, thus leading to an overly-accommodating monetary policy without addressing the source of the widening gap. Therefore, the central bank may account for the impact of climate change by correcting the potential output (i.e., deflating it by the expected damage) and turning (49) into:

$$y_t = \frac{Y_t}{Y_t^* \left(1 - \psi_{t-1}\right)} - 1, \tag{51}$$

where ψ_{t-1} is the estimated output loss due to climate change, set equal to the damage observed in the previous period $t-1$ (see Section 3.7).

3.6 The government

For the sake of simplicity, the government performs some basic functions to ensure the proper functioning of the monetary system. In particular, it recapitalizes banks in financial distress and collects taxes on firms' profits and households' income to keep public debt under control. The latter is entirely held by the central bank (an entity owned by the government) in the form of high-powered money, which constitutes banks' reserves. Accordingly, a fiscal expansion due to a bank bailout increases both the public debt and the monetary base (i.e., banks' reserves), consistent with the standard practice of *lender of last resort* observed during periods of financial distress.

Therefore, the public debt (and banks' reserves) B_t decreases with tax collection and increases with bank recapitalization expenditures:

$$B_t = B_{t-1} + G_t - T_t^W - T^f - T_t^b, \tag{52}$$

where $T_t^W = \sum_{f=1}^{\mathcal{N}^F} \tau_t w_t N_{f,t}$, $T_t^f = \sum_{f=1}^{\mathcal{N}^F} T_{f,t}$, and $T_t^b = \sum_{b=1}^{\mathcal{N}^B} T_{b,t}$ are the total taxes collected on labor income, firms' profits, and banks' profits, respectively. The public expenditure G_t on bank recapitalization is determined by (41), and the government does not incur interest expenses on public debt since the central bank fully monetizes its value.

Lastly, to keep public debt under control, the government sets the tax rate τ_t as a function of the difference between the current volume of debt B_t and a minimum (initial) value B_1,[10] relative to nominal GDP:

$$\tau_t = \max\left(0, -\psi_G \frac{B_{t-1} - B_1}{\bar{p}_{t-1} Y_{t-1}}\right), \tag{53}$$

where ψ_G is a parameter capturing the speed of debt convergence toward B_1.[11]

[10] We keep a minimum value because of the reserve requirement ratio γ_{CB}. See Section 3.3.

[11] Notice that (52) and (53) implies: $B_t - B_{t-1} \approx G_t - \psi_G(B_{t-1} - B_1)$.

3.7 The climate module

To replicate the effects of exogenous climate shocks in the model, we introduce a simple climate module based on Economides and Xepapadeas (2018). Since we are testing a set of locally enforced adaptation strategies (i.e., acting at a country level), we assume an exogenous path for global CO_2 emissions. Indeed, by applying national measures, only a few countries can have a significant impact on aggregate CO_2 emissions and, even then, the effects would be limited. Nevertheless, this assumption does not affect our research, which aims to analyze the macro-financial aspects of different adaptation policies.

The global temperature is a linear function of cumulate emissions $\check{E}_t$, with the temperature anomaly relative to pre-industrial levels ΔT_{t+1} being equal to:

$$\Delta T_{t+1} = \gamma_E \check{E}_t, \tag{54}$$

where γ_E is a fixed parameter (i.e., the Transient Climate Response to cumulative Emissions — TCRE).

We obtain historical emissions for the period 1850–2020 from the *Our World in Data CO_2 and Greenhouse Gas Emissions* dataset. We then forecast possible future paths of CO_2 emissions following Bazzana et al. (2024), i.e., by simulating them in a Stochastic Impacts by Regression of Population, Affluence, and Technology (STIRPAT) framework.[12] Figure 2 displays the evolution of quarterly CO_2 emissions until the end of the century.

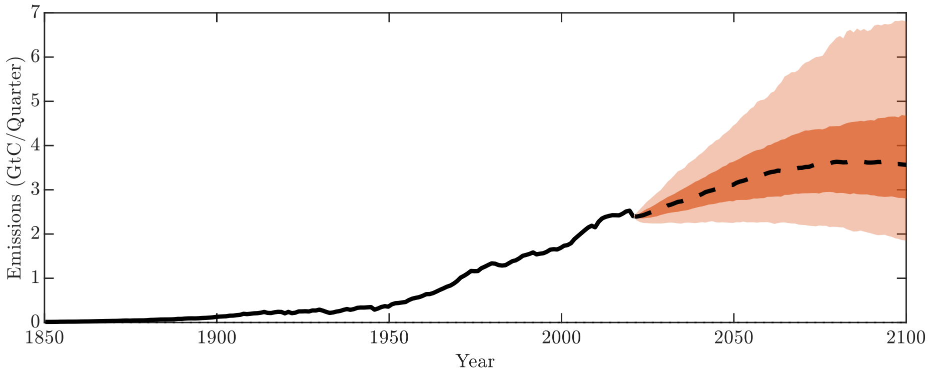
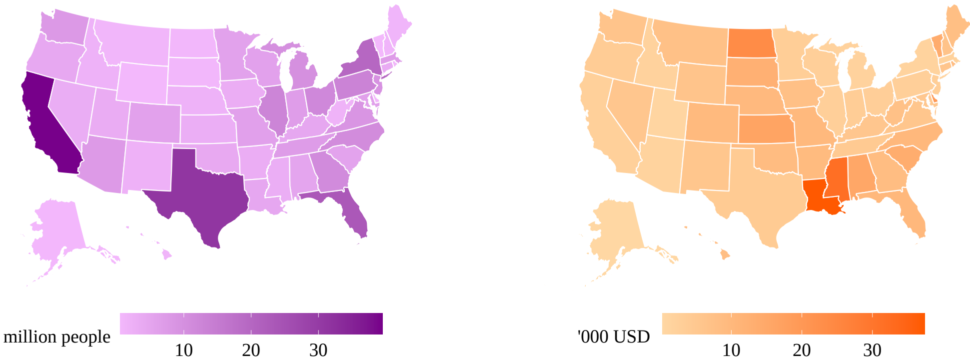


Figure 2: Forecasts for CO_2 emission paths up to 2100

Note: The black solid line shows real data until 2020, while the dashed line indicates the median of all STIRPAT forecasts until the end of the century, with the shaded areas representing 50% and 90% confidence intervals.

To introduce climate shocks in the model, we choose a well-known aggregate damage function from the DICE 2023 model (Barrage and Nordhaus, 2024) due to its specificity

[12]The forecast of future global emissions requires an econometric setting that accounts for the linkages between population (P), GDP per capita (A), emission intensity (T, here in terms of CO_2 emissions per unit of output), and potential lag effects. By employing a Vector Autoregression (VAR) model, we consider all these interlinkages. World population and real GDP data for the 1965–2020 timeframe are retrieved from *World Bank Open Data*. Friedlingstein et al. (2022) supply data on regional and global CO_2 emissions for the same period (*The Global Carbon Budget*).



(a) U.S. population

(b) Damage per capita

Figure 3: Population and climate damages in the U.S.

Sources: U.S. Census Bureau, `https://www.census.gov`; The International Disaster Database, `https://www.emdat.be/`.

to the U.S. calibration. The average damage affecting labor productivity ψ_t is thus a quadratic function of the temperature anomaly:

$$\psi_t = \varphi_1 \Delta T_t + \varphi_2 \Delta T_t^2. \tag{55}$$

However, population and climate damages are distributed unevenly throughout the U.S., and it is fundamental to account for these regional differences when studying firm-level adaptation. Figure 3 highlights the heterogeneity in population, distribution, and damage intensity across U.S. states. Although large populous states (such as California, Texas, and Florida in Figure 3a) are increasingly subject to frequent droughts, fires, and storms, damage intensities (Figure 3b) show a different picture, with the Deep South and certain areas of the Midwest being disproportionately affected by natural disasters.

For this reason, at the beginning of every simulation, we randomly assign firms to each U.S. state in proportion to their respective shares of the U.S. population. Then, by employing the *International Disaster Database* dataset,[13] we identify the state-level intensity of climate-related extreme weather events (as damage per capita, ι_s) and assign it to each firm accordingly ($\iota_f = \iota_s \forall f \in s$). Subsequently, by defining the unitary damage ω_t at time t:

$$\omega_t = \psi_t \left(\frac{\sum_{f=1}^{\mathcal{N}^F} \iota_f}{\mathcal{N}^F} \right)^{-1}, \tag{56}$$

we distribute the aggregate damage ψ_t to each state as follows:

$$\psi_{s,t} = \iota_s \cdot \omega_t. \tag{57}$$

[13]We use data from the 1975–2024 period, due to availability. See `https://www.emdat.be/`.

In this way, the average damage is consistent with the DICE 2023 model, but its allocation is more representative of geographical asymmetries in climate damage incidence.

Lastly, when damages are homogeneous, all firms assigned to the same state experience an identical decline in labor productivity, then $\forall f \in s$:

$$\psi^{Hom}_{f,t+1} = \psi_{s,t+1}. \tag{58}$$

However, in the real world, damages are rarely homogeneous, as climate change manifests as localized extreme weather phenomena of varying intensity, such as floods, droughts, hailstorms, and hurricanes. As a consequence, the productive capacity of the firms hit by climate disasters is often not just impaired but also halted entirely. In light of these considerations, we follow Bazzana et al. (2024) and assume $\psi_{s,t}$ to be the probability faced by each firm f within state s to be hit by localized extreme weather events as follows:

$$\psi^{Het}_{f,t+1} = \begin{cases} 1 & \text{with probability } \psi_{s,t+1}, \\ 0 & \text{otherwise.} \end{cases} \tag{59}$$

In other words, firms directly affected by an extreme weather event induced by climate change experience a complete loss of labor productivity, whereas unaffected agents continue their production activities without disruption.

4 Policy experiments

To assess the macro-financial effects of climate-related damages and adaptation strategies, we design three experiments, each tested under the assumption of homogeneous and heterogeneous climate shocks, as described in Section 3.7. Table 1 summarizes the characteristics of each scenario.

The *Baseline* scenario is the benchmark for all the experiments. In this setting, the central bank follows a standard monetary policy, there is no climate damage, and no adaptation strategies are implemented.

The CD — *Climate Damage* — scenario introduces climate-related shocks, modeled as either homogeneous (CD1) or heterogeneous (CD2). These two cases serve as additional benchmarks, allowing us to compare the effects of various adaption strategies under the assumption of different damage types.

The CDY — *Climate Damage + Output gap correction* — scenario (CDY1 in the case of homogeneous damages, and CDY2 for heterogeneous ones) introduces an output gap correction mechanism by the central bank. This policy affects the ability of the monetary authority to discern the source of financial distress, deciding to tackle only internal — i.e., endogenous — downturns.

The CDF — *Climate Damage + Firms' adaptation* — scenario tests the ability of firms to adapt their behavior based on recent experience of climate-related damages, allowing them to adjust their input demand accordingly. As in previous scenarios, we account for both homogeneous (CDF1) and heterogeneous (CDF2) damages.

We evaluate each scenario through 250 Monte Carlo simulations, each initialized with a different random seed. Each simulation spans 5,000 periods, with the first 4,000 discarded as burn-in to allow the system to stabilize. The remaining 1,000 periods correspond to the quarterly observations covering the 1850–2100 timeframe. We introduce damage shocks and policy experiments starting from the year 2020.

Table 1: Scenarios tested

Label	**Climate damage**	**Central bank correction**	**Firms adaptation**
Baseline	–	–	–
$CD1$	Homogeneous	–	–
$CD2$	Heterogeneous	–	–
$CDY1$	Homogeneous	✓	–
$CDY2$	Heterogeneous	✓	–
$CDF1$	Homogeneous	–	✓
$CDF2$	Heterogeneous	–	✓

4.1 Results and discussion

Before examining the macro-financial effects of adaptation strategies to climate change, we first analyze the impact of homogeneous and heterogeneous climate shocks (i.e., the CD1 and CD2 scenarios, respectively). The left panels of Figure 4 show the percentage variation of real GDP from the *Baseline* scenario in the presence of climate damages. The top panel corresponds to the homogeneous case (CD1), whereas the bottom panel illustrates the effects of heterogeneous shocks (CD2).

In both cases, the DICE 2023 damage function determines an end-of-century average real GDP loss between 8% and 12% for a median increase in pre-industrial temperature of 3.7°C, in line with standard IAM literature (Tol, 2018). However, heterogeneous shocks produce larger output losses by 2100 and a more pronounced decline in firms' equity (Table 2, first row). Although aggregate lending also contracts under heterogeneous damage, the reduction is smaller, leading to an overall increase in firms' leverage. That reflects an increased demand for liquidity: by disrupting firms' production and revenue flows in the short term, heterogeneous climate shocks intensify firms' reliance on external debt financing to cover operating expenses. Accordingly, the increased leverage and interest rates negatively affect firms' profitability and net worth.

Moving to adaptation policies, Figure 4 shows the percentage variation of real GDP from the *Baseline* scenario under the assumption of output gap correction by the central bank (CDY1 and CDY2 — central panels) and firm-level adaptation (CDF1 and CDF2 — right panels). Both strategies yield positive effects when compared to the *Baseline* scenario (CD1 and CD2 — left panels). When damages are homogeneous, the degree

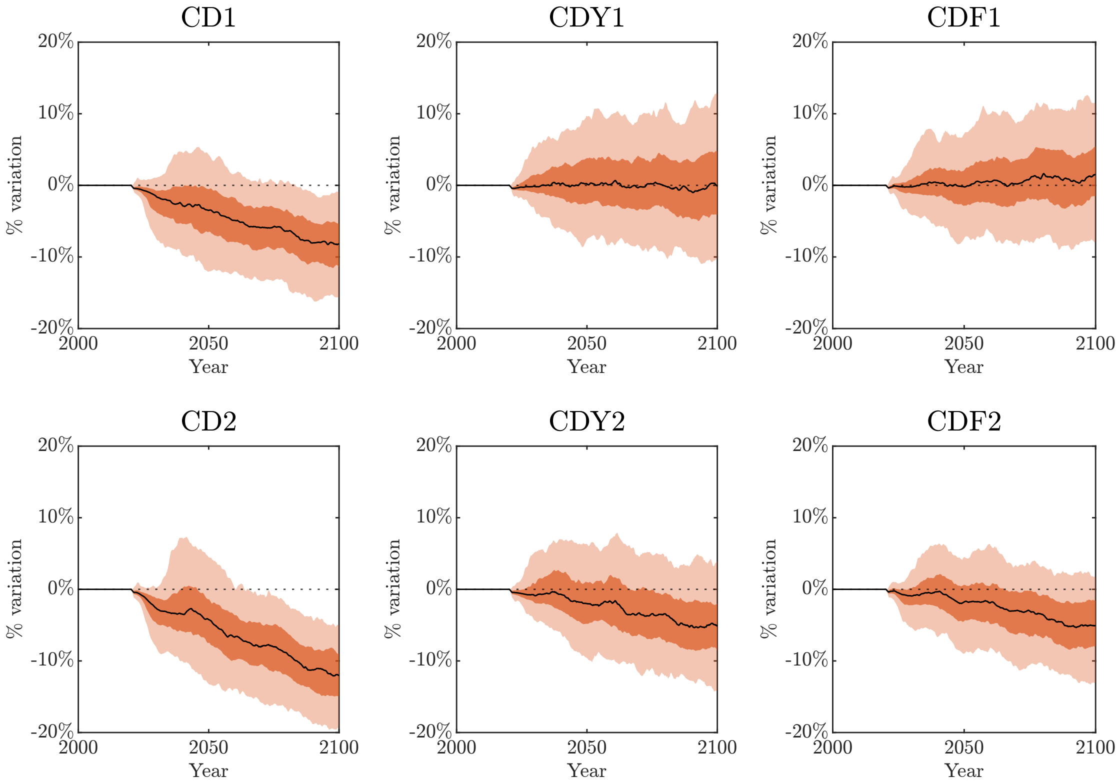


Figure 4: Real GDP variation with output gap correction and firm adaptation

Note: Percentage variation from to the *Baseline* scenario. Median (solid black line) plus 50% and 90% confidence intervals (shaded areas).

of uncertainty surrounding their magnitude is lower, thus improving the accuracy of both firms' and the central bank's responses. In this case, the average output fully recovers from climate damages (see Figure 4, top panels). The central bank's output gap correction (CDY1) brings production back to *Baseline* levels, while firms' adaptation (CDF1) proves even more effective, resulting in a long-term output increase of around 2% (see Table 2, third row). These results highlight the potential of bottom-up adaptation when climate impacts are predictable: by adjusting labor demand, firms can effectively offset the economic consequences of homogeneous shocks.

Once again, heterogeneous shocks lead to worse economic performance. Output gap correction (CDY2) produces more limited, albeit sizable, benefits compared to the homogeneous case (CDY1). Still, output losses are reduced by half, and these results provide further support to the increasing literature connecting climate change and monetary policy, highlighting the benefits of a climate-aware central bank (Campiglio, 2016; Matikainen et al., 2017; Dafermos et al., 2018). Firms' adaptation (CDF2) produces similar results. When climate damages increase, firms cannot account for the additional exposures to this risk. In the case of heterogeneous damages, larger shocks raise the prob-

Table 2: Economic and financial performance in 2100

Scenario	Output		Loans		Leverage		Firms' equity		Banks' equity	
	Hom.	Het.	Hom.	Het.	Hom.	Het.	Hom.	Het.	Hom.	Het.
CD	−8.2% (5.0%)	−12.1% (5.2%)	−13.9% (4.1%)	−5.4% (4.2%)	1.2% (3.6%)	7.1% (3.7%)	−17.2% (12.4%)	−28.3% (11.1%)	−21.0% (9.8%)	−15.1% (10.1%)
CDY	−2.2% (8.0%)	−5.8% (6.9%)	3.2% (3.8%)	8.7% (4.6%)	−1.6% (5.0%)	6.0% (4.4%)	12.9% (24.5%)	−13.5% (15.7%)	0.7% (13.2%)	0.9% (12.8%)
CDF	1.5% (6.7%)	−5.1% (5.4%)	0.7% (3.9%)	−2.0% (11.3%)	−0.2% (4.8%)	5.8% (4.7%)	3.7% (22.2%)	−20.9% (13.2%)	−3.2% (11.2%)	−13.7% (11.2%)

Note: Mean and standard deviation (in brackets) of aggregate sales and financial metrics in 2100. Percentage deviation from *Baseline* scenario under homogeneous (Hom. — scenarios 1) and heterogeneous (Het. — scenarios 2) climate shocks.

ability of default of larger firms, leaving the door open to large-scale financial contagion through the credit market channel. These results are consistent with the microeconomics literature on firm adaptation (for a comprehensive review, see Grover and Kahn, 2024), in which climate risk uncertainty can determine a loss of aggregate output (for instance, in Jia et al., 2022, flood risk lowered U.S. GDP by 0.52% in 2018, with 80% of the reduction stemming from expectations, and only 20% from direct flood damages).

While the two adaptation strategies yield similar results in terms of real GDP (Table 2, first column), they produce different effects on aggregate financial conditions. Regardless of the scenario under consideration, heterogeneous climate damages lead to an overall increase in firms' leverage (Table 2, third column). That reflects the sudden disruption in production caused by weather shocks, which requires firms to seek additional liquidity to offset both the lost revenues and the ongoing operating expenses. Nevertheless, there is a significant difference in the source of liquidity between the two approaches. The output gap correction (CDY2) leads to a tighter monetary policy, boosting banks' profitability and credit supply (Table 2, second and last columns), which translates into a monetary expansion and a partial recovery in firms' nominal equity (Table 2, fourth column). On the contrary, firm-level adaptation (CDF2) leads firms to rely more on internal resources accumulated during "good" periods (i.e., without shocks), thus eroding their net worth and negatively affecting the banking sector (Table 2, last two columns). In this regard, a more climate-aware central bank may benefit the credit sector but require closer monitoring of financial stability due to increased dependence of firms on debt financing.

Lastly, examining the impact on the distribution of firms' net worth (Figure 5), the central bank's output gap correction (CDY1 and CDY2) produces a positive effect for most firms. Nevertheless, the bottom percentiles are still disproportionately affected by climate damages and higher cost of credit. In contrast, firms' adaptation with homogeneous damages (CDF1) yields milder improvements but still redirects the median net worth distribution towards the *Baseline*. However, the CDF2 scenario does not significantly improve the CD2 outcome, showing the inability of single firms to handle climate

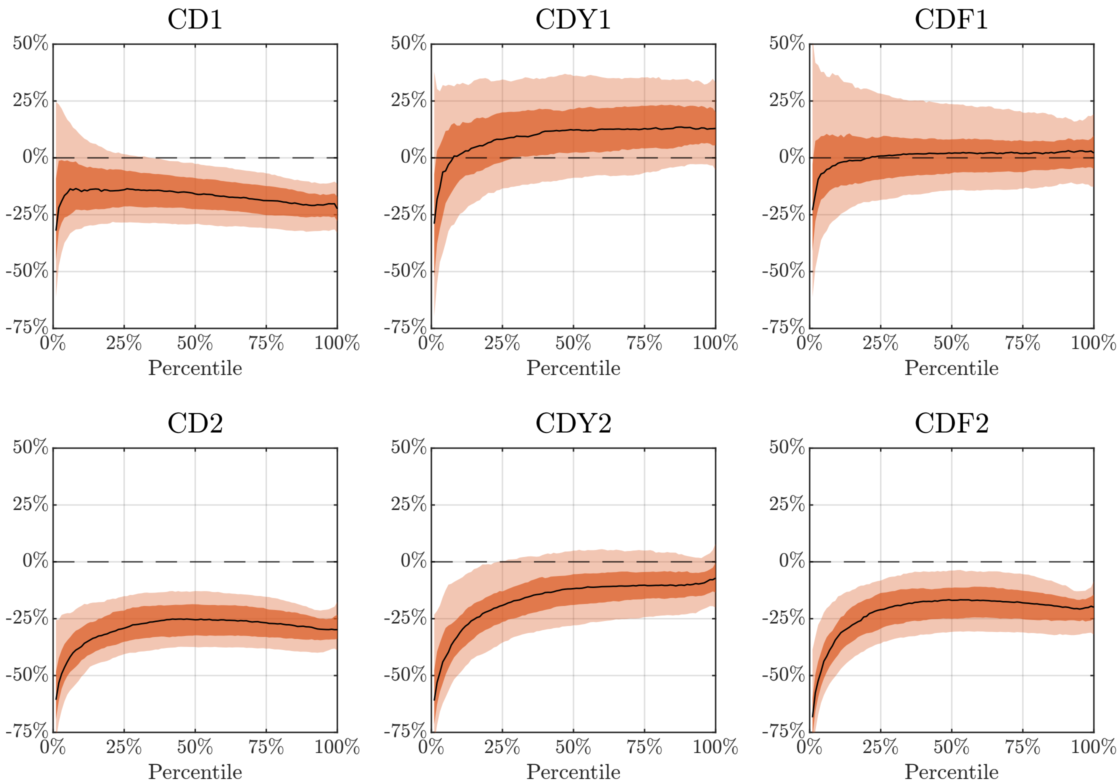


Figure 5: Shift function of firms' net worth distribution

Note: Percentage variation from the *Baseline* scenario in firms' net worth distribution for different percentiles. Median (solid black line) plus 50% and 90% confidence intervals (shaded areas).

shocks when they manifest as severe, abrupt events, compared to constantly increasing but somewhat predictable productivity losses. This translates into the loss of firms' equity shown in Table 2.

5 Conclusions

In this study, we develop a Stock-Flow-Consistent Agent-Based Integrated Assessment model, characterized by a financial accelerator, to examine the macro-financial effects of climate change and different adaptation strategies. This framework allows us to analyze the economic, financial, and distributional consequences of homogeneous and heterogeneous climate shocks in a stylized yet realistic setting. Our experiments include climate-aware monetary policy and a firm-level adaptation strategy whereby firms internalize climate damages by modifying their input demand.

Our results indicate that while both types of shock lead to significant GDP losses by the end of the century, heterogeneous climate damages produce a larger output decline and an increase in firms' leverage. Indeed, by disrupting firms' production and revenue flows in the short term, heterogeneous shocks intensify firms' reliance on debt financing to cover operating expenses. Accordingly, the increased leverage and interest rates negatively affect their profitability and net worth, with implications for systemic financial risk.

Adaptation efforts by the central bank and individual firms can mitigate some of these effects. When damages are homogeneous, and thus more predictable, both strategies are effective in restoring production levels. However, their efficacy diminishes under heterogeneous shocks, where uncertainty affects the capacity of both monetary policy and firms to respond effectively. The model also accounts for spatial asymmetries in climate risk exposures. Indeed, the geographical location of firms affects their vulnerability to extreme climate events. Those operating in more exposed areas may achieve a higher level of awareness surrounding climate risks, thus making them more prepared to face these events (Burlig et al., 2024). However, in the face of localized but abrupt climate events (i.e., heterogeneous damages), firms still struggle to adapt effectively.

Lastly, while the GDP outcomes are similar across adaptation strategies, their financial implications differ significantly. On the one hand, central bank intervention supports the banking sector by raising interest rates and boosting credit supply. As a result, economic agents experience a smaller contraction in their balance sheets, but at the cost of increased indebtedness. On the other hand, firm-level adaptation relies more on internal resources, thus eroding firms' net worth and negatively affecting the banking sector.

In light of these findings, as climate impacts intensify over time, it is fundamental to equip firms, especially smaller ones, with the necessary tools to adapt, either by improving their forecasting capabilities or expanding access to adequate insurance mechanisms. At the same time, it is increasingly urgent that policymakers adjust their financial policy tools to directly address their effects (see also Campiglio, 2016; Dafermos et al., 2018; Lamperti et al., 2021). Lastly, extreme weather events are expected to inflate corporate leverage and debt. That raise additional concerns amid the recent global surge in debt accumulation (Kose et al., 2021; Furceri et al., 2025) and underscore the need for closer monitoring of financial stability in the future.

Our work has some limitations that leave room for future extensions. First, our focus on country-level policies led us to adopt exogenous GHG emission paths, ignoring the potential feedback loops between climate change and technological improvements (Carrión-Flores and Innes, 2010). Further, including endogenous technical change may affect macro-stability by altering the firms' input productivity and requirements. Moreover, climate shocks may produce their effects on long-term growth in such a setting, thus enhancing their impact. Lastly, we may also consider climate impacts on capital, which may lead us to better assess the more permanent effects of climate damage.

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A Aggregate stocks and flows

Table A.1: Balance-Sheet Matrix

	Workers	**Entrepreneurs**	**Firms**	**Banks**	**Government & Central Bank**	Σ
Fixed capital			$+K^N$			$+K^N$
Reserves/Bonds				$+B$	$-B$	0
Deposits	$+Dep_w$	$+Dep_e$	$+Dep_f$	$-Dep_b$		0
Loans			$-L$	$+L$		0
Equities		$+A_e$	$-A_f$	$-A_b$		0
Balance (net worth)	$-NW_w$	$-NW_e$	0^*	0^*	$-NW_g$	$-K^N$
Σ	0	0	0	0	0	0

*: we assume that equities correctly price (i.e., they coincide with) the new worth of firms/banks.

Table A.2: Transactions-Flows Matrix

	Workers	**Entrepreneurs**	**Firms**		**Banks**		**Government &**	Σ
			Current	**Capital**	**Current**	**Capital**	**Central Bank**	
Transactions								
Consumption	$-pC_w$	$-pC_e$	$+pC$					0
Net investment			$+pI - \delta_F K^N$	$-pI + \delta_F K^N$				0
Wages	$+wN + c_B L$		$-wN$		$-c_B L$			0
Taxes	$-T_w$		$-T_f$		$-T_b$		$+T$	0
Loan interests			$-iL$		$+iL$			0
Public exp.					$+G$		$-G$	0
Profits, firms		$+Div_f$	$-\Pi_f$	$+\Delta A_f$				0
Profits, banks		$+Div_b$			$-\Pi_b$	$+\Delta A_b$		0
Flow of funds								
Δ Reserves/Bonds						$-\Delta B$	$+\Delta B$	0
Δ Deposits	$-\Delta Dep_w$	$-\Delta Dep_e$		$-\Delta Dep_f$		$+\Delta Dep_b$		0
Δ Loans				$+\Delta L$		$-\Delta L$		0
Loan defaults				$+S$		$-S$		0
Σ	0	0	0	0	0	0	0	0

B Model initialization

We initialize the model by assuming unitary wages and prices ($w_1 = 1$ and $p_{f,1} = 1$), a zero tax rate ($\tau_1 = 0$), no government spending ($G_1 = 0$), and equilibrium in all markets. The economy is in steady state, there are no liquidity constraints, and agents are homogeneous within their respective types (i.e., they correspond to a representative firm, bank, or entrepreneur, depending on their type). Lastly, each firm employs one unit of labor ($N_{f,1} = 1$) and is connected to a random bank. The risk-free interest rate is set equal to its long-term value ($i_1^{taylor} = r^* + \pi^*$).

The following equations define the nonlinear system through which we initialize the simulated economy. We categorize them into three categories: real-financial transactions, balance sheets, and behavioral rules. The system's solution provides the initial values of all variables, as well as the parameters of the production function (θ_1 and θ_2) and the dividend rate (η_B), implicitly determined by the model's assumptions. Since we are analyzing a static equilibrium, we adopt a simplified notation in this section.

B.1 Real-financial transactions

Starting from firms, (17) defines individual profits:

$$\Pi_f = p_f \left(C_f + I_f - \delta_F K_f\right) - wN_f - i_f L_f. \tag{B.1}$$

Since the economy is in steady state, investments equal capital depreciation:

$$I_f = \delta_F K_f, \tag{B.2}$$

and profits are entirely distributed as dividends:

$$\Pi_f = Div_f. \tag{B.3}$$

Moving to banks, we derive aggregate sectoral profits from (37):

$$\mathcal{N}^B \Pi_b = \mathcal{N}^F \left(i_f - c_B\right) L_f, \tag{B.4}$$

which are entirely paid in the form of dividends:

$$\Pi_b = Div_b. \tag{B.5}$$

Lastly, households consume all their income, equal to dividends from firms and banks for entrepreneurs:

$$\mathcal{N}^F pC_e = \mathcal{N}^F Div_f + \mathcal{N}^B Div_b, \tag{B.6}$$

and wages for workers:

$$pC_w = \mathcal{N}^F \left(wN_f + c_B L_f\right). \tag{B.7}$$

The previous equations imply the equilibrium in the consumer goods market, namely:

$$C_w + \mathcal{N}^F C_e = \mathcal{N}^F C_f, \tag{B.8}$$

which we exclude from the system since redundant.

B.2 Balance sheets

Balance sheet equilibrium requires that total assets (the left-hand side of equations from this point onward) equal total liabilities and net worth. For firms, this condition implies:

$$Dep_f + pK_f = A_f + L_f, \tag{B.9}$$

while for the entire banking system we have:

$$\mathcal{N}^F L_f + B = \mathcal{N}^F Dep_f + \mathcal{N}^F Dep_e + Dep_w + \mathcal{N}^B A_b. \tag{B.10}$$

At the same time, the aggregate net worth of entrepreneurs must equal the sum of banks' and firms' equity, along with personal deposits:

$$\mathcal{N}^F A_f + \mathcal{N}^B A_b + \mathcal{N}^F Dep_e = \mathcal{N}^F NW_e. \tag{B.11}$$

On the contrary, households' net worth is entirely held in the form of deposits:

$$Dep_w = NW_w. \tag{B.12}$$

Lastly, the government and the central bank must satisfy the following identity:

$$0 = NW_g + B. \tag{B.13}$$

Taken together, these equations imply the following condition for aggregate net worth:

$$\mathcal{N}^F pK = \mathcal{N}^F NW_e + NW_w + NW_g, \tag{B.14}$$

which we exclude from the system since redundant.

B.3 Behavioral rules

The behavioral rules of firms, banks, and consumers complete the system of equations.

Starting with firms, (26) defines dividends distribution:

$$Div_f = \eta_F \left(\Pi_f + A_f\right). \tag{B.15}$$

At the same time, the production function (1) implies the following conditions:

$$Y_f = \min\left(\theta_1 K_f, \theta_2 N_f\right) \Rightarrow \begin{cases} Y_f = \theta_1 K_f, \\ Y_f = \theta_2 N_f. \end{cases} \tag{B.16}$$

For calibration purposes, we complement the labor-based condition, $Y_f = \theta_2 N_f$, with its empirical counterpart (see C.4 in Section C.1):

$$w_F N_f = \gamma_F p Y_f, \tag{B.17}$$

where γ_F is the share of revenues paid as labor costs. Lastly, firms hold the minimum amount of deposits required to advance wage payments:

$$Dep_f = wN_f. \tag{B.18}$$

Moving to banks, (42) defines the dividend distribution rule:

$$Div_b = \eta_B \left(\Pi_b + A_b \right). \tag{B.19}$$

In addition, banks' equity must satisfy capital (29) and reserve (30) requirements:

$$\nu_{CB} \mathcal{N}^F L_f = \mathcal{N}^B A_b, \tag{B.20}$$

$$B = \gamma_{CB} \left(\mathcal{N}^F Dep_e + \mathcal{N}^F Dep_f \right). \tag{B.21}$$

Lastly, interest rates on loans follow (31):

$$i_f = i_b^* = r^* + \pi^* + \delta_B + \alpha_B \ell_f - \zeta_B n_b, \tag{B.22}$$

where the risk factors reduce to $n_b = 1$ and $\ell_f = L_f/(A_f + L_f)$ since all banks and firms are assumed to be homogeneous.

Concluding with entrepreneurs and households, they fuel consumption by resorting to their net worth. Entrepreneurs consume a fixed portion of their wealth (43):

$$pC_e = \iota_E NW_e, \tag{B.23}$$

while households fully deplete their net worth (46):

$$NW_w = 0. \tag{B.24}$$

C Calibration and validation

The model employs several free parameters that we classify into three categories: calibrated, estimated, and initialized. Section C.1 describes the calibration procedure for the parameters that have a direct counterpart in U.S. data. Section C.2 illustrates the estimation of unobservable structural parameters, and Section C.3 validates the obtained results. Lastly, we set the remaining values (e.g., the parameters of the production function, θ_1 and θ_2) such that the simulated economy starts in steady state, at market equilibrium, and respecting stock-flow consistency and behavioral rules (initialized parameters, see Section B).

C.1 Calibration

We calibrate the parameters with a direct counterpart in U.S. time series from multiple sources covering the last 25 years (i.e., *Federal Reserve Economic Data* and *U.S. Bureau of Economic Analysis*). Since the simulated economy has a quarterly frequency, we set them to replicate the annual averages observed in the data. Moreover, to generate sufficient market interactions while maintaining simulation tractability, we assume a reasonable number of firms (and entrepreneurs, $\mathcal{N}^F = 1000$) and banks ($\mathcal{N}^B = 10$).

Starting from producing firms, we compute the quarterly depreciation rate of capital, δ_F, as the difference between annual gross (GOS_f) and net (NET_f) operating surplus of non-financial companies between 1997 and 2021, divided by their total liabilities and equity (i.e., $L_f + A_f$):

$$\delta_F = \frac{1}{4}\frac{GOS_f - NET_f}{L_f + A_f}. \tag{C.1}$$

Similarly, since dividends equal net profits in equilibrium, we determine the quarterly dividend rate as follows:

$$\eta_F = \frac{NET_f/4}{A_f + NET_f/4}. \tag{C.2}$$

Under the same assumption, entrepreneurs' propensity to consume out of net worth ι_E is equal to the ratio:

$$\iota_E = \frac{(NET_f + NET_b)/4}{A_e + (NET_f + NET_b)/4}, \tag{C.3}$$

where A_e represents the net financial assets of households (and rest of the world), while NET_f and NET_b are the net operating surplus of financial and non-financial business, respectively.

Under the assumption of initial unitary wages ($w_1 = 1$) and prices ($p_{f,1} = 1$), labor demand (see 15) implies the following relationship between the labor share γ_F (i.e., the aggregate compensation of employees divided by total value added) and productivity θ_2:

$$\theta_2 = \frac{1}{\gamma_F}\frac{w_1}{p_{f,1}} = \frac{1}{\gamma_F}. \tag{C.4}$$

Concerning the banking sector, we consolidate the aggregate balance sheet and revenues of the financial sector through the *Input-Output* and *Issuer-to-Holder* tables to avoid double counting. We then compute the cost parameter c_B as the quarterly-adjusted annual compensation of employees over total financial assets. By contrast, we derive the macroprudential parameter (ν_{CB}) from the *Basel III International Regulatory Framework for Banks*. Lastly, we estimate the parameters of the interest rate rule from the *World Bank Global Financial Development* (WBGFD) dataset. In particular, we regress the (quarterly adjusted) net interest margin of U.S. banks (NIM_t) on the aggregate leverage (LEV_t, computed as risk-weighted over total assets) and market concentration (CON_t)[14] between 2000 and 2020. To control for autocorrelation (ρ_B), we estimate the following econometric model via maximum likelihood:

$$NIM_t = \delta_B + \alpha_B LEV_t + \zeta_B CON_t + \rho_B \left(NIM_{t-1} - \delta_B - \alpha_B LEV_t - \zeta_B CON_t\right) + \varepsilon_t, \quad \text{(C.5)}$$

where $\varepsilon_t \sim N(0, \sigma^2)$ is an error term following a normal distribution with zero mean and variance σ^2, while δ_B, α_B and ζ_B are the values of the interest rate rule in (31). Table C.1 reports the obtained results.

Table C.1: Maximum Likelihood, using observations 2001-2020 ($T = 20$).

HAC standard errors

	Estimate	**Std. Error**	z	**p-value**	
δ_B	0.006743	0.001464	4.604	< 0.0001	$***$
α_B	0.004612	0.001801	2.560	0.0105	$**$
ζ_B	-0.000029	0.000002	-12.643	< 0.0001	$***$
ρ_B	0.557988	0.177261	3.148	0.0016	$***$

Log-likelihood	132.2292	Akaike criterion	-256.4583
Schwarz criterion	-252.4754	Hannan-Quinn	-255.6808

We conclude by setting the parameters of the public sector. Starting from the central

[14] Under the assumption that banks' loans ($L_{b,t}$) follow a lognormal distribution with mean $\mu_{B,t}$ and variance $\sigma^2_{B,t}$, the aggregate value (i.e., the weighted average) of $n_{b,t}$ in (31) is approximately equal to:

$$\sum_b \left(n_{b,t} \cdot \frac{L_{b,t}}{\sum_b L_{b,t}} \right) = \frac{\sum_b L^2_{b,t}/\mathcal{N}^B}{\left(\sum_b L_{b,t}/\mathcal{N}^B\right)^2} \approx \frac{E[L^2_{b,t}]}{E[L_{b,t}]^2} = \frac{\exp(2\mu_{B,t} + 2\sigma^2_{B,t})}{\exp(2\mu_{B,t} + \sigma^2_{B,t})} = \exp(\sigma^2_{B,t}).$$

Since the WBGFD dataset provides the share of assets held by the three and five largest banks in the U.S. ($s_{\bar{b},t}$ with $\bar{b} = \{3, 5\}$), we can derive this value under the previous assumption of lognormality, namely:

$$\exp(\sigma^2_{\bar{b},t}) = \exp[\Phi^{-1}(s_{\bar{b},t}) + (1 - p_{\bar{b},t})] \quad \text{with} \quad \bar{b} = \{3, 5\},$$

where $p_{\bar{b},t}$ is the percentile of the three and five largest banks in the size distribution, and Φ^{-1} is the inverse of a normal cumulative distribution function. Therefore, we can approximate market concentration, CON_t, through the simple average:

$$CON_t \approx \frac{1}{2} \sum_{\bar{b}=\{3,5\}} \exp\left[\Phi^{-1}(s_{\bar{b},t}) + (1 - p_{\bar{b},t})\right].$$

bank, we assume a constant monetary base, corresponding to a zero inflation target π^*. Further, we compute the natural interest rate r^* as the average quarterly fed funds rate minus realized inflation between 1986 and 2024. We set the remaining values of the Taylor rule (y_{CB}, π_{CB}, and ρ_{CB}) following López-Salido et al. (2020). Lastly, we determine the reserve requirement γ_{CB} through the observed ratio between the monetary aggregate M2 and total currency in circulation in the period 1960–2020, while we assume a five percent annual reduction rule of public debt (i.e., $\psi_G = 0.05/4$).

C.2 Estimation

We estimate the model's unobservable parameters (β_B, θ_B, ω_B, β_D, θ_D, ω_D, ρ_F, μ_F) using Approximate Bayesian Computation (ABC — see Drovandi et al., 2015, for a review). The aim is to identify the (probabilistic) vector of structural parameters $\boldsymbol{\theta} \in \mathbb{R}^d$ that maximizes the artificial likelihood evaluated on the empirical data $\mathbf{Y}^R = \{\mathbf{y}_t^R\}_{t=1}^{T^R}$. For this purpose, we choose the demeaned[15] U.S. quarterly time series of nonfinancial business leverage, CPI inflation, real GDP growth, and Federal Funds rate over the period 1952–2019, resulting in $T^R = 242$ observations (source: *Federal Reserve Economic Data*).

Following Grazzini et al. (2017), we define the artificial likelihood as:

$$\mathcal{L}\left(\boldsymbol{\theta}; \mathbf{Y}^R\right) \propto f(\mathbf{Y}^R \mid \mathbf{X}_{t-1}^R, \boldsymbol{\theta}) = \prod_{t=1+l}^{T^R} f\left(\mathbf{y}_t^R \mid \mathbf{x}_{t-1}^R, \boldsymbol{\theta}\right), \tag{C.6}$$

where $\mathbf{x}_{t-1}^R = \left(\mathbf{y}_{t-1}^R, \ldots, \mathbf{y}_{t-l}^R\right)$. The function $f\left(\mathbf{y}_t^R \mid \mathbf{x}_{t-1}^R, \boldsymbol{\theta}\right)$ is the Kernel Density Estimator (KDE) of the joint distribution of the empirical data $\mathbf{y}_t^R \in \mathbb{R}^4$, conditional on the parameter vector $\boldsymbol{\theta}$ and l lagged observations to capture autocorrelation.[16] Accordingly, for each parameter vector $\boldsymbol{\theta}$, we simulate the time series $\mathbf{Y}^S(\boldsymbol{\theta}) = \{\mathbf{y}_t^S(\boldsymbol{\theta})\}_{t=1}^{T^S}$ of length $T^S = S + H \cdot T^R$ from the model, discard the initial $S = 1{,}500$ periods as burn-in and use the remaining $H \cdot T^R$ data points to compute the KDE of empirical observations.[17] We set $H = 20$, a multiple of the original data length, to enhance estimation precision.

Given our optimization target (C.6), we employ the two-step procedure developed by Ciola et al. (2022) to improve computational speed and set prior distributions for subsequent Bayesian estimation.

Firstly, we find a neighborhood of the global optimum trough *Particle Swarm Optimization* (PSO), a gradient-free algorithm that optimizes a multivariate function (in this case: $f(\mathbf{Y}^R \mid \mathbf{X}_{t-1}^R, \boldsymbol{\theta}) : \mathbb{R}^d \to \mathbb{R}$) by exploiting the information coming from N^{PSO} particles roaming the parameter space. At each iteration $j = 1, \ldots, J^{PSO}$, the values of the best-performing particle are used to determine the next direction of the entire swarm, eventually leading to the convergence towards the optimum. To maximize parameter space exploration, we run $Z^{PSO} = 50$ independent replicas, each employing $N^{PSO} = 40$

[15] Since long-term growth is neither the focus of our study nor a feature of the model, we do not address growth dynamics in this context.

[16] We set $l = 4$ to account for both quarterly and annual dynamics while leaving minimal residual autocorrelation.

[17] In other words, $f(\mathbf{Y}^R \mid \mathbf{X}_{t-1}^R, \boldsymbol{\theta}) = f\left(\mathbf{Y}^R \mid \mathbf{X}_{t-1}^R, \mathbf{Y}^S(\boldsymbol{\theta})\right)$.

particles over $J^{PSO} = 100$ iterations. We set the inertia weight ($\omega^{PSO} = 0.75$) and learning factors ($c_1^{PSO} = c_2^{PSO} = 1.5$) of the algorithm following standard practices (see Wang et al., 2017, for a review).

Figure C.1 illustrates the results of this step. While some parameters (such as β_D, ρ_F, and μ_F) exhibit clear convergence toward specific values, others display substantial variability across runs. To reduce variance, we keep only the best-performing draw for each particle (represented by the black lines and shaded areas in Figure C.1), allowing us to focus on the most informative regions of the parameter space.

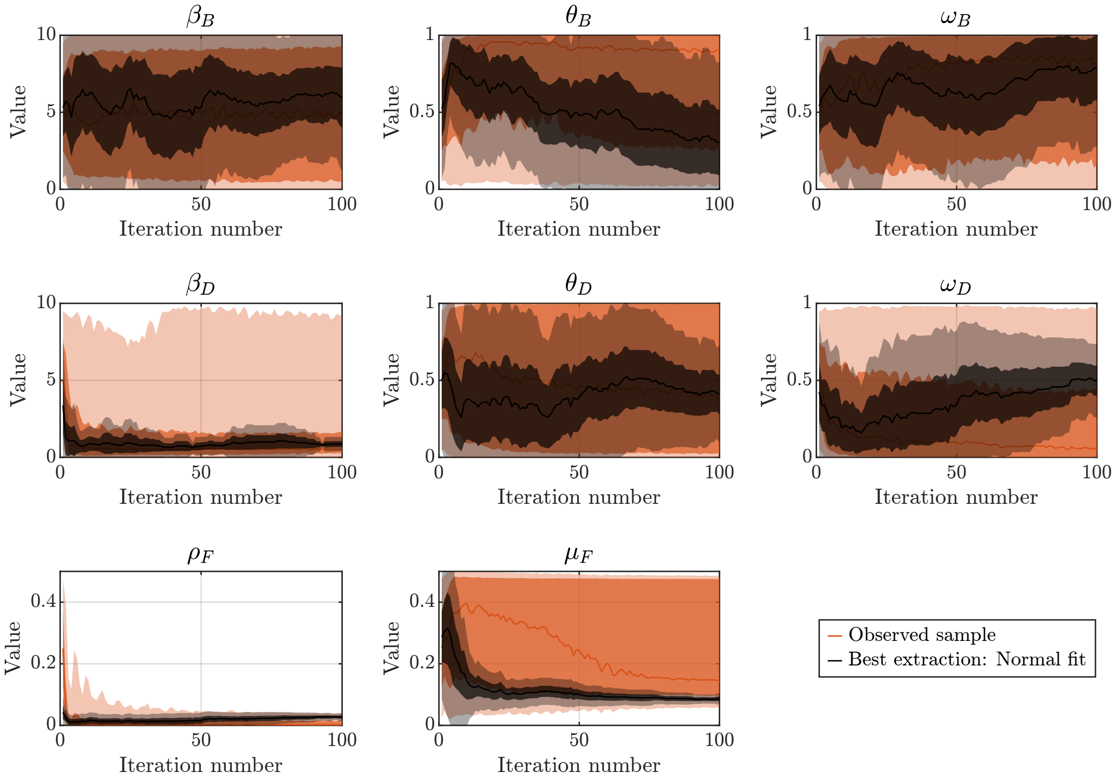

Figure C.1: PSO algorithm evolution

Note: Parameter values' evolution for $N^{PSO} = 40$ particles over $Z^{PSO} = 50$ independent replicas. Medians (solid lines) plus 50% and 90% quantile bands (shaded areas) for the full set (red) and the best-performing draw for each particle (black).

Secondly, we generate a sample $\{\boldsymbol{\theta}^j\}_{j=1}^{J^{MH}}$ from the artificial distribution $\mathcal{L}\left(\boldsymbol{\theta}; \mathbf{Y}^R\right)$ using a Random Walk Metropolis-Hastings algorithm (RWMH — Metropolis et al., 1953; Hastings, 1970), with the following acceptance probability:

$$\alpha\left(\boldsymbol{\theta}^*, \boldsymbol{\theta}^{j-1}\right) = \min\left[1, \frac{f(\mathbf{Y}^R \mid \mathbf{X}_{t-1}^R, \boldsymbol{\theta}^*) p\left(\boldsymbol{\theta}^*\right) q\left(\boldsymbol{\theta}^{j-1} \mid \boldsymbol{\theta}^*\right)}{f(\mathbf{Y}^R \mid \mathbf{X}_{t-1}^R, \boldsymbol{\theta}^{j-1}) p\left(\boldsymbol{\theta}^{j-1}\right) q\left(\boldsymbol{\theta}^* \mid \boldsymbol{\theta}^{j-1}\right)}\right], \tag{C.7}$$

where $p\left(\boldsymbol{\theta}\right) = \mathcal{N}\left(\boldsymbol{\mu}, \Sigma\right)$ is the prior distribution, a multivariate normal whose parameters $\boldsymbol{\mu}$ and Σ are computed from the best-performing draw of the previous step. At each iteration j, we sample the candidate vector $\boldsymbol{\theta}^*$ from the proposal distribution $q\left(\boldsymbol{\theta}|\boldsymbol{\theta}^{j-1}\right) = \mathcal{N}\left(\boldsymbol{\theta}^{j-1}, \Sigma\right)$, a multivariate normal centered at the previous draw — as in standard RWMH algorithm — and with the same covariance of the prior distribution.

Figure C.2 illustrates the outcome of this step. Similar to the PSO algorithm, some parameters (such as β_D, θ_D, ω_D, ρ_F, and μ_F) display well-behaved posterior distributions, while others remain weakly identified. Acknowledging the limitations of our estimation, we use the simple average of the posterior distributions (reported in Table D.1) as a reference point for simulations.

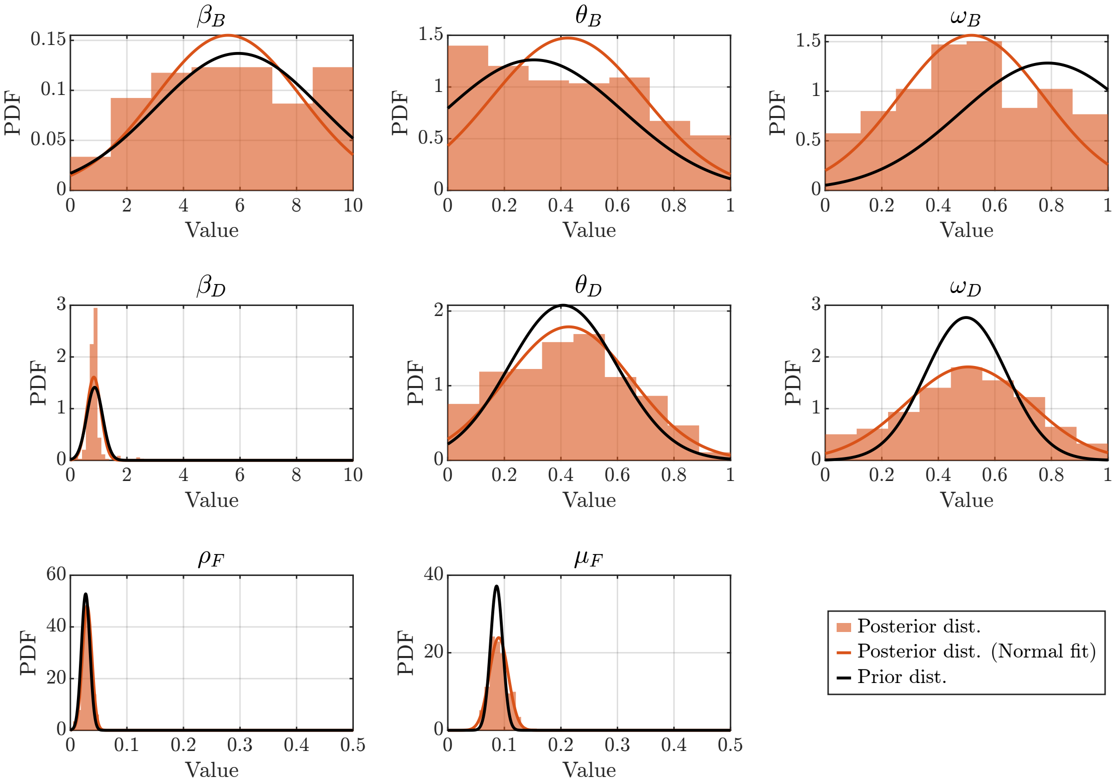

Figure C.2: RWMH algorithm

Note: Prior (black lines) and posterior (red line and histogram) distribution of structural parameters. Results for $N^{RW} = 250$ particles after $J^{RW} = 100$ iterations.

C.3 Validation

To assess whether the model is useful or not to analyze policy options, we first need to verify that its output is coherent with the empirical evidence. This happens when the model is able to reproduce a set of stylized facts that are relevant to the purposes of the research question. In Figure C.3 we show the cross-correlation (with respect to output growth rate) of the main simulated macro series (in orange) against the ones we obtain from real U.S. data (in blue) on which the model is calibrated.

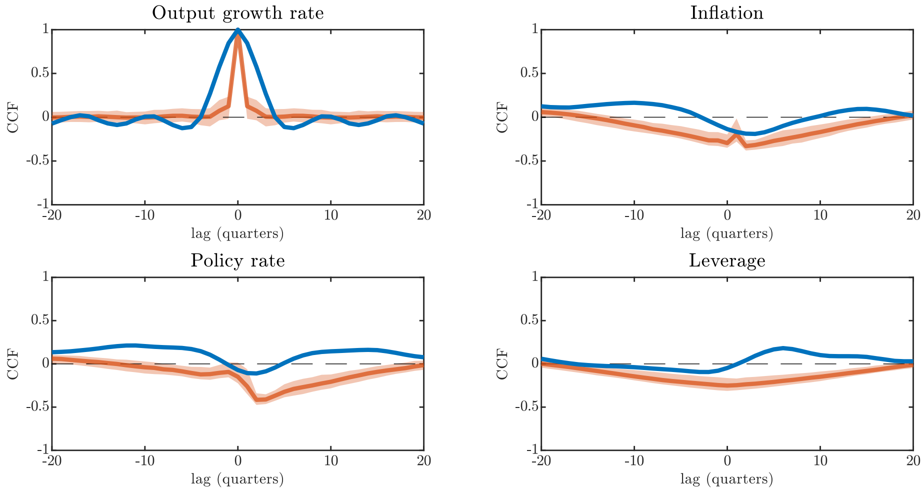

Figure C.3: Time series cross-correlations with output growth rate.

Note: the cross-correlations displayed are obtained from real (blue) and simulated (orange) data. Simulated data refer to the *Baseline* scenario.

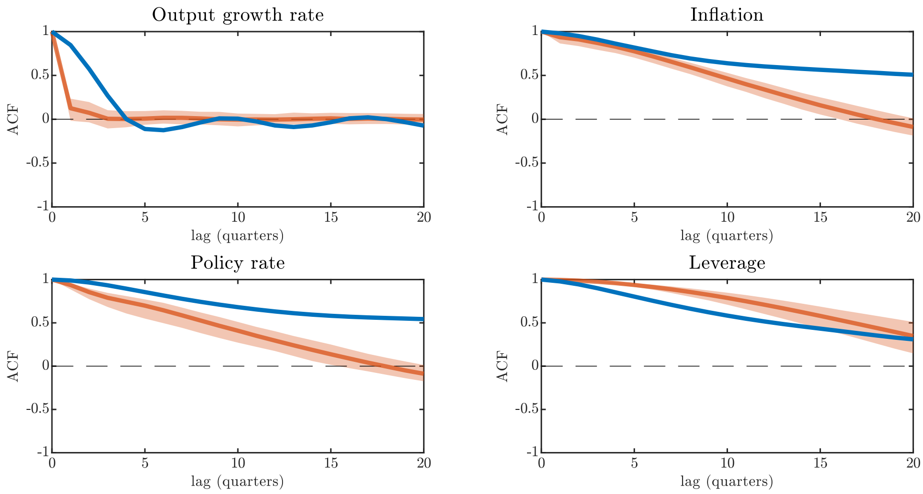

Figure C.4: Time series autocorrelation.

Note: the autocorrelations displayed are obtained from real (blue) and simulated (orange) data over 20 lags. Simulated data refer to the *Baseline* scenario.

We can see how simulated cross-correlations over twenty quarters lags mostly follow the ones we obtain from historical data (using the same time series employed for the estimation process in Appendix C.2). Further, if we consider autocorrelation of GDP growth rate, inflation, policy rates, and leverage displayed in Figure C.4 we notice some distinct similarities between real and simulated data (especially below ten quarters lag). Moreover, we verify in Table C.2 the second, third, and fourth moments for the same macro series, both real and simulated. The results from the simulated series are in line with historical data. In general, this analysis confirms that the output of our model is able to reproduce the same statistical properties as the macro-series from the real U.S. economy.

Table C.2: Standard deviation, skewness, and kurtosis of real and simulated series.

	Output growth rate		**Inflation**		**Policy rate**		**Leverage**	
	Real	Sim.	Real	Sim.	Real	Sim.	Real	Sim.
Std Dev	0.0057	0.0114	0.0053	0.0053	0.0075	0.0057	0.0486	0.0349
Skewness	-0.4804	-0.6909	1.4689	1.0646	0.7751	1.3049	-0.2258	-0.3623
Kurtosis	3.5020	5.2853	4.6433	3.2704	3.5952	3.9558	2.4181	2.3857

Note: Standard deviation, skewness, and kurtosis for simulated data are computed as the mean second, third, and fourth moments across all simulations.

Finally, we verify that the firms' net worth distribution is long-tailed and right-skewed (Axtell, 2001; Gaffeo et al., 2003). Figure C.5 plots the median Decumulative Distribution Function (DDF) and firms' net worth across all *Baseline* simulations.

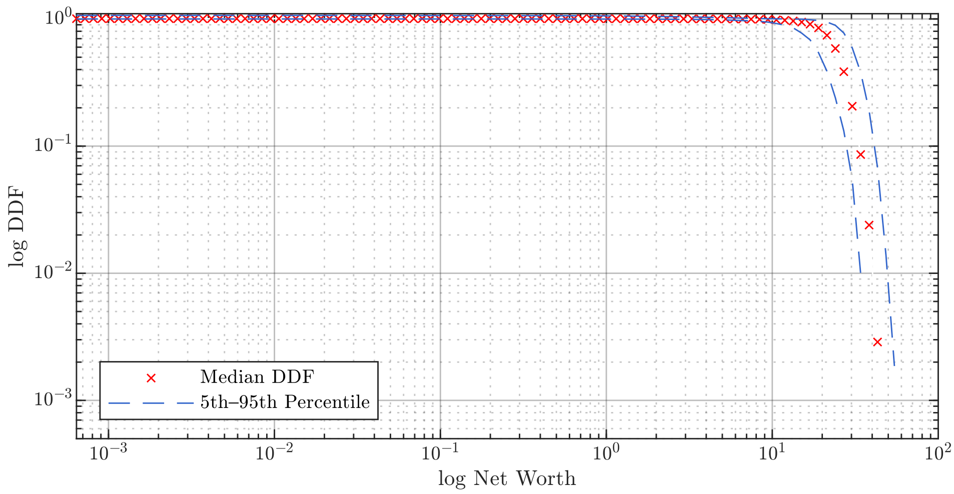

Figure C.5: Median net worth distribution.

Note: log-log plot of median Decumulative Distribution Function (DDF) and net worth of firms in the *Baseline* scenario. The dashed lines represent the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles.

D Model parameters and initial values

Table D.1: Model parameters

Parameter	Description	Value
Firms		
$\mathcal{N}^F$	Number of firms	1,000
δ_F	Depreciation rate of capital	0.012
γ_F	Share of labor cost	0.543
ρ_F	Adjustment speed of production target	0.0297
μ_F	Adjustment speed of prices	0.0901
η_F	Dividend rate of firms	0.0290
Banks		
$\mathcal{N}^B$	Number of banks	10
δ_B	Systemic risk pricing	0.00674
α_B	Sensitivity of interest rates to firm-specific risk	0.00461
ζ_B	Sensitivity of interest rates to bank-specific risk	0.00003
β_B	Intensity of choice	5.5799
θ_B	Demand persistence	0.4245
ω_B	Relative weight of credit supply	0.5172
c_B	Labor cost in the banking sector	0.007
Entrepreneurs		
$\mathcal{N}^E$	Number of entrepreneurs	1,000
ι_E	Propensity to consume out of net worth	0.012
Consumers		
β_D	Intensity of choice	0.8307
θ_D	Demand persistence	0.4276
ω_D	Relative weight of market share	0.5051
Central bank		
r^*	Natural interest rate	0.002
π^*	Inflation target for monetary policy	0.000
y_{CB}	Weight of output gap for monetary policy	0.810
π_{CB}	Weight of inflation for monetary policy	2.000
ρ_{CB}	Partial adjustment of monetary policy	0.560
γ_{CB}	Reserve requirement on total deposits	0.100
ν_{CB}	Macroprudential parameter	0.080
Government		
ψ_G	Tax adjustment	0.0125
Climate module		
γ_E	TCRE parameter	0.002522
φ_1	DICE 2023 damage function parameter	0.0
φ_2	DICE 2023 damage function parameter	0.003467

Table D.2: Initialized values

Parameter	Description	Value
Firms		
w_1	Wages	1
$p_{f,1}$	Initial prices	1
$N_{f,1}$	Initial labor allocation	1
$K_{f,1}$	Initial capital endowment of firms	28.2909
θ_1	Productivity of capital	0.0651
θ_2	Productivity of labor	1.8416
$Y_{f,1}$	Initial production	1.8416
$K_{f,1}^N$	Initial nominal capital endowment of firms	28.2909
$Dep_{f,1}$	Initial deposits of firms	1
$L_{f,1}$	Initial loans to firms	19.7696
$A_{f,1}$	Initial net worth of firms	9.5214
Banks		
i_1^{taylor}	Initial policy rate	0.002
$i_{b,1}^f$	Initial interest rate	0.011
η_B	Dividend rate of banks	0.0479
$A_{f,1}$	Initial net worth of banks	158.15645
B_1	Initial aggregate reserves	2,020.8879
Entrepreneurs		
$Dep_{e,1}$	Initial deposits of entrepreneurs	19.2089
$A_{e,1}$	Initial net worth of entrepreneurs	30.3118

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