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Firm heterogeneity and regional economic recovery from environmental shocks ☆

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ABSTRACT

Destructive climate-induced extreme events increasingly affect people and economies worldwide. Their impacts are widely studied using both empirical and simulation methods. Yet, the scientific debate on whether environmental shocks induce growth spurts, leave persistent scars on the economy, or barely have any long-term effects, remains unresolved. Here, we show how differences in aggregate economic dynamics can be explained by heterogeneity at the firm-level, specifically the distribution of damages among firms and different productivity level of affected firms. We employ a novel multi-regional economic agent-based model, where firms in one of the regions are struck by a climate-induced shock. We find that these firm-level heterogeneities have significant effects on aggregate economic dynamics, with long-run outcomes ranging from full recovery to modest growth, and even to persistent depression. Our results show that shocks to clusters of economic activity can have outsized impacts on regional economies compared to a representative distribution of impacts. This highlights fundamental problems with conventional aggregated analysis of physical climate risks and of overall costs of climate change, suggesting that policy-focused analysis could be misguided when omitting a granular representation of economic agents.

1. Introduction

Climate change and population growth increase hazard risks, with escalating costs for societies (IPCC, 2022). Some costly examples from 2024 include hurricane Helene in the United States (219 casualties, 56b US$ in damages) or the Valencia torrential flash flood in Spain (232 casualties, 11b US$ in damages) (Munich Re, 2025). The increasing frequency of such events emphasizes the need for policies that reduce vulnerabilities and exposure, speed up recovery after these hazards materialize, and increase anticipatory climate adaptation actions. For such policies to be effective, a comprehensive understanding of the economic mechanisms shaping physical climate risks is required. However, current empirical findings on (long-run) impacts of climate-induced impacts on economies provide opposing evidence, ranging from post-shock growth to persistent scarring (Botzen et al., 2019; Klomp and Valckx, 2014; Lazzaroni and van Bergeijk, 2014). Factors that are found to influence an economy's reaction to a shock include the level of development (Felbermayr and Gröschl, 2014; Noy, 2009), the state of the business cycle (Hallegatte and Ghil, 2008) or its agglomeration level (Taberna et al., 2022). Notably, the micro-structure such as network connectivity between critical sectors (Baqaee and Farhi, 2019; Di Noia et al., 2025) and firms (Henriet et al., 2012; Otto et al., 2017; Boehm et al., 2019; Diem et al., 2022) are also reported as factors defining the magnitude of physical climate risks.

So far, the impact of firm-level heterogeneities – such as firm-specific damages and firm characteristics – on economic recovery has received little attention in economic analysis. In most conventional models, including Integrated Assessment Models, Input–Output Models and Computable General Equilibrium models, the level of aggregation and a representative assumption prohibit studying the effect of such heterogeneities. These models provide valuable insights in macro trends. Yet, they may underestimate climate damages due to (among other factors) their reliance on representative agents (Farmer et al., 2015; Stern, 2013). Furthermore, it is difficult to incorporate spatial heterogeneities in exposure and damages (Hallegatte et al., 2024), hindering the distributional economic analysis of climate shocks. However, firm-level heterogeneities are widely present.

In the context of climate-induced damages, two types of firm-level heterogeneities are of particular interest: (1) the different degrees of exposure of firms to environmental shocks due to spatial clustering of economic activity, and (2) the different types of firms being exposed to floods — in particular low and highly productive firms. Firstly, various firms face different exposure to specific climate-induced shocks. For

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example, consider the most widespread and costly hazard: flooding. Just as shocks from heavy rainfall, river, or coastal flooding are spatially clustered, so is economic activity and the infrastructure footprint of human development (Fujita et al., 1999; De Dominicis et al., 2013; Henderson et al., 2018). These economic clusters often spatially overlap in riverbanks, deltas and coastlines (Kocornik-Mina et al., 2020; Lin et al., 2024; Rentschler et al., 2023), since these waterways reduce firms' transportation costs. Development of economic clusters in these risky areas is further exacerbated by the reinforcing effect of government protection aimed at protecting high-stakes areas (Gandhi et al., 2022; Husby et al., 2014; Mård et al., 2018), known as the 'safe development paradox' (Di Baldassarre et al., 2019; Fusinato et al., 2024). As such, while this protection makes floods less likely to occur, it renders it to be more devastating *when* it occurs (Etkin, 1999). This spatial clustering means that flood exposure differs significantly between firms within the same region. Secondly, firms that are exposed to environmental shocks may differ from those that are not. Historic agglomeration generates technological and knowledge spillovers that increase productivity (Duranton and Puga, 2004) and attract more productive firms, leading to economic clusters being typically populated by more productive firms (Baldwin and Okubo, 2006) which often significantly contribute to the output of the whole region (Ahlfeldt et al., 2024). Consequently, this may steer many highly productive firms to locate in potentially climate-sensitive areas, which – given that large, highly productive firms can disproportionately impact the overall economy when shocked (Gabaix, 2011) — could have large impacts on regional economies.

The goal of this paper is to explore if these differences in the impacts of environmental shocks on diverse firms may explain why some economies thrive and others experience persistent output drops after an environmental shock. In other words, we strive to test if these micro-level heterogeneities explain the emergence of qualitatively different aggregate post-shock economic dynamics. Specifically, our research questions enquire how these macro-dynamics are impacted by: (RQ1) the degree by which damages are concentrated among few firms or spread across many firms — simulating the clustering versus spreading of economic activity across space; and (RQ2) the extent to which more/less productive are prone to be shocked — simulating the selection of more/less productive firms in risky areas. When addressing these research questions, we trace the dynamic pathways of economy-wide development following a disaster to assess whether this shock induces economic growth, has no effect, or scars the economy by inducing a long-term output decline.

Computational agent-based models (ABMs) excel in aiding such disaggregated economic analysis (Tesfatsion, 2006; Arthur, 2006; Dawid and Delli Gatti, 2018; Arthur, 2021; Axtell and Farmer, 2025). For environmental and climate change economics specifically, ABMs allow studying impacts of heterogeneities (Lamperti et al., 2018; Castro et al., 2020; Balint et al., 2017), increased behavioral realism (Safarzyńska et al., 2013), uncertainties and granular damage functions (Farmer et al., 2015; Waldrop, 2018; Taberna et al., 2020; Filatova and Akkerman, 2026). For floods in particular, ABMs have been used to study the effect of short-run adjustments and economic recovery dynamics (Naqvi and Rehm, 2014), propagation of climate shocks through supply networks (Willner et al., 2018), economic agglomeration dynamics (Taberna et al., 2022), regional economic effects of private adaptation uptake (Taberna et al., 2023a,b), cascading effects and distributional impacts (Bachner et al., 2024), and interactions between public protection and population density (Haer et al., 2020).

Leveraging these advances in ABM, we develop a novel agent-based computational economics model – EMERGO (Emergent Macro-Economic dynamics in Regional economies Governed by climatic shOcks) – to answer our research questions. EMERGO represents an economy with two regions: one exposed to environmental disasters and one safe. The regions are populated by heterogeneous firms and households who interact with each other bilaterally via goods, services and labor markets, and may endogenously decide to migrate. The macro-dynamics emerge from these micro-interactions, rather than being modeled directly. This enables us to trace how a change at the agent-level – e.g. firm's capital stock destruction, buffering effect of inventories and cash holdings, or firm's investment or migration decision – propagates to aggregate outcomes. We calibrate EMERGO based on the empirical archetype of an industrialized economy, and run a series of computational experiments to address RQ1 and RQ2 by quantifying the effect of heterogeneous impacts on short-term recovery and long-term economic development.

Our analysis finds that shocks with identical initial aggregate damages lead to either full recoveries or persistent scarring, purely based on the distribution of damages among firms. Particularly, more spatially concentrated shocks, and shocks that affect more productive firms have larger and highly persistent negative impacts on the directly affected region, and even create economic scars for the entire national economy. While our analysis remains stylized, it captures the generic mechanisms that link granular impacts and real-world firm heterogeneity to emergent macro trends, enhancing economic understanding of shocks. These insights can inform policies that affect the distribution of economic activity over space — and with it, society's exposure to climatic hazards. Furthermore, these insights add a possible explanation to the ongoing scientific debate by explaining the contradictory empirical results on economic effects of climate shocks.

The paper proceeds as follows. Section 2 provides an overview of the two-region computational economic model with heterogeneous agents, and describes the experimental setup used to answer our research question. Section 3 presents a baseline reaction of multi-region economy to a climatic shock, and dives into the results of our experiments. Finally, Section 4 discusses these results and indicates directions for future research.

2. Methods

The EMERGO model represents a closed macroeconomy, consisting of two connected regions. Here, we provide an overview of the model and describe the agent behaviors in detail. In Appendix A the model steps, institutional agents and market interactions are described in detail. EMERGO grounds on the key blocks of related economic ABMs (Dawid and Delli Gatti, 2018; Taberna et al., 2022), and advances them to trace how micro-level firm behaviors and heterogeneity shape macro-dynamics in the presence of shocks in different time frames. We clarify the novel methodological elements of EMERGO in Appendix C.

2.1. Model overview

EMERGO models dynamics among two types of heterogeneous economic agents: firms ($i \in \mathcal{F}$) and households ($j \in \mathcal{H}$), and two institutional agents: the government and the mutual fund (Fig. 1). These dynamics are modeled over $T = 600$ steps, where each step represents a month. Firms use labor and capital goods to produce one of three outputs, forming sectors ($s \in \mathcal{S}$): consumer goods (CG), consumer services (CS) and capital goods (KG). Households consume CG and CS, and provide labor to firms in exchange for wages. Both CG and CS are non-durable, whereas KG is a durable investment good. The government taxes households' incomes and firms' profits, and pays out unemployment benefits (UB) to unemployed households, and social benefits (SB) to all households. The mutual fund collects dividend payments from firms, pays out capital income to households, and provides venture capital investments to startup firms. Their behaviors are described in Appendix A.2.

All firms and households reside in either of the two regions, and can migrate between them driven by purely economic reasons. At initialization, we set both regions to have equal population. All outputs (CS, CG, KG) as well as labor (L) are exchanged in markets, where CG and KG are tradable (i.e. can be sold in a different region as where

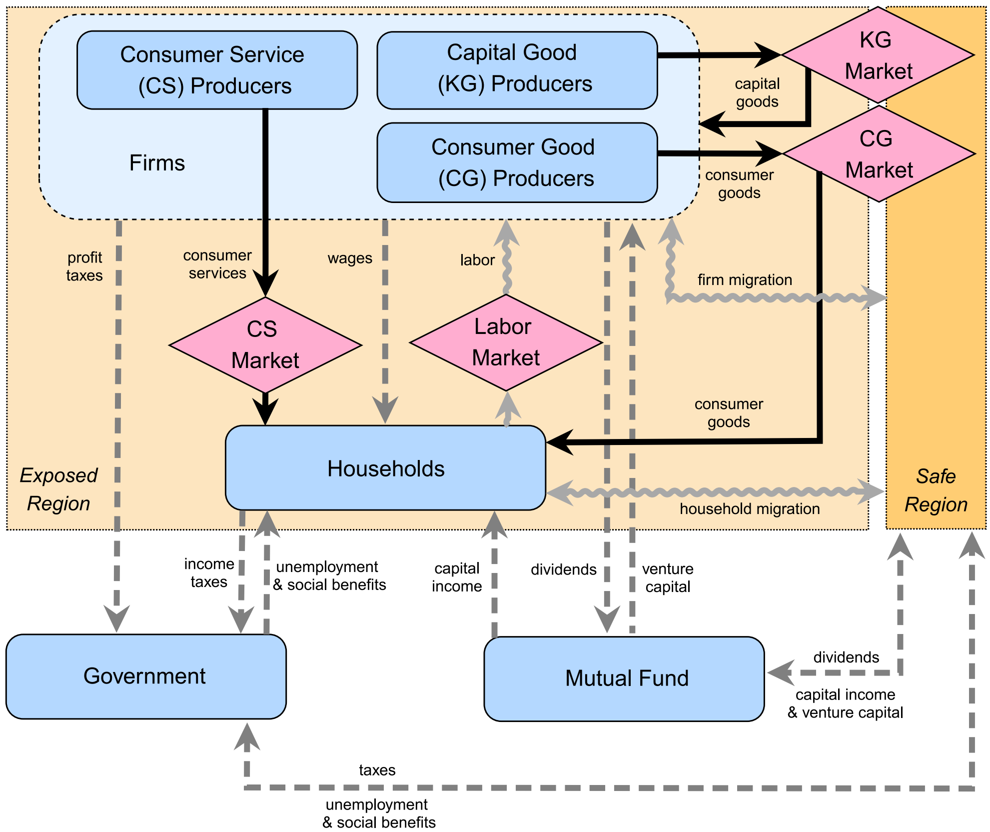


Fig. 1. Overview of agent classes, (market) interactions and regions present in the EMERGO model. Arrows present flows of goods and services (solid), money (dashed) and agents (squiggly). Note that each region – exposed and safe – simulates all these different agents and own markets following the same structure as illustrated in details for the exposed region.

they are produced) and L and CS can only be exchanged in the region of production.

One of the regions (named *exposed*) can be struck by a shock, for example a flood, whereas the other region is not directly exposed (named *safe*), and is only indirectly affected through trade and migration. The flood shock is a 'tail event', meaning it has a large impact, but is also rare, yet with climate changing becoming more likely. This rarity means agents lack past experience with such events and do not incorporate its future possibility in their economic expectations and decisions. So, firms in EMERGO cannot perfectly anticipate a shift of climatic hazards towards more tail-events, which is in line with empirical findings of insufficient adaptation uptake by firms (Goldstein et al., 2019). The macroeconomic dynamics of this model emerge directly from the dynamics of local states, behaviors and microeconomic interactions of the agents. This gives rise to both short-run post-shock out-of-equilibrium dynamics as agents recover, as well as the economy converges to the new long-run steady state. Crucially, emergent macrodynamics, including the out-of-equilibrium pathways, enable studying how agent-level heterogeneities affect post-shock outcomes in the long run. Furthermore, agent behavior is affected by flows (goods, income, expenses) and stocks (inventories, cash holdings, capital goods), which endogenously give rise to supply and financial frictions.

The EMERGO model is calibrated to represent an archetypical industrialized economy, where the model parameters are primarily set using representative studies and datasets for EU countries and the US. The economy is characterized by a high employment share in services and low unemployment level. The calibration of the model parameters is extensively described in Section 3 of the supplementary material.

2.2. Agents

All agent have to base their decisions on limited, often local information and making use of limited computational capabilities. Their decisions are therefore based on behavioral heuristics (Simon, 1955) that are simpler than those approximating economically optimal actions. For instance, a firm cannot derive its global optimal equilibrium price, but it can infer it should increase prices if it sells more than it produces. Collectively, in the absence of shocks, these microeconomic behaviors drive the macroeconomy to a state where GDP is stable, and unemployment is only frictional — i.e. a statistical equilibrium at macro-level with possible small micro adjustments.

2.2.1. Firms

Each firm $i \in \mathcal{F}$ produces output using labor and capital as inputs with Leontief technology:

$$q^{+}_{i,t} = \min\left\{ A_i L_{i,t}, \frac{K_{i,t}}{\kappa_s} \right\}, \tag{1}$$

where $q^{+}_{i,t}$ is production capacity of firm i and time t, A_i the idiosyncratic productivity level, $L_{i,t}$ the labor stock from the employees, $K_{i,t}$ the stock of capital from the machine inventory, and κ_s the capital intensity of the sector s in which the firm operates. Here, $\kappa_{\mathrm{KG}} > \kappa_{\mathrm{CG}} > \kappa_{\mathrm{CS}}$. The use of Leontief technology means no substitution is possible between labor and capital. This is especially relevant in the immediate disaster aftermath, as substitution is unlikely in the short run (Hallegatte and Vogt-Schilb, 2019). Firms acquire labor by employing households, and capital by investing in capital goods.

Each firm has an idiosyncratic level of labor productivity A_i, following a truncated Lognormal distribution. This means it is fat-tailed and right-skewed, and the majority of firms have a similar lower level of labor productivity, while there are a few firms with a higher level. Firms with higher labor productivity produce at lower costs, and therefore grow larger than their less productive counterparts. This makes the distribution of labor productivity in the firm population the primary driver of endogenously evolving firm size heterogeneity. This relation has both a theoretical and empirical foundations (Melitz, 2003; Bartelsman et al., 2005). The truncation of the productivity distribution at $A^{\min}$ is meant to avoid firms entering with a near-zero chance of survival.

The firm has to set its desired production capacity $\tilde{q}^+_{i,t}$ (also determining its target labor stock $\widetilde{L}_{i,t}$ and target capital stock $\widetilde{K}_{i,t}$), the price level of its output $p_{i,t}$ and the wage it offers to attract new employees $w^o_{i,t}$. Because the firm does not have full information on its customer preferences and competitors, it cannot directly set $\{\tilde{q}^+_{i,t}, p_{i,t}, w^o_{i,t}\}$ to profit-maximizing quantities. Instead, the firm uses *adjustment heuristics* (Fagiolo et al., 2019), where it adjusts $\{\tilde{q}^+_{i,t}, p_{i,t}, w^o_{i,t}\}$, sees how profit rates, demand for output and the number of applicants change, after which it adjusts again. As such, the firm *slowly* adjusts its behavior to a more optimal level. Such adaptive behaviors are especially relevant after a large shock, when this optimal level may change drastically, and the firm has to adjust its behaviors to the new circumstances.

The firm can adjust $p_{i,t}$ and $w^o_{i,t}$ more easily than its production capacity $q^+_{i,t}$, as the latter requires hiring new employees and investing in more capital goods. We therefore assume the firm updates $p_{i,t}$ and $w^o_{i,t}$ every $\theta^p = \theta^w = 3$ months, whereas $q^+_{i,t}$ is updated every $\theta^q = 12$ months.[1] These 'fast' and 'slow' processes work in tandem to let the firm search for its (near-)optimal production levels (Leijonhufvud, 2006) through the adjustment rules we describe below. An overview of the adjustment process can be seen in Fig. A.7.

Firstly, every year ($\theta^q = 12$) the firm assesses whether this current production level is optimal. For this, it estimates its marginal monthly profit rate (i.e. its estimate of the profit rate earned by producing an additional unit of output):

$$\hat{\pi}_{i,t} = \frac{p_{i,t} - w^o_{i,t}/A_i}{\bar{p}^K_{i,t}\kappa_s/\tilde{\varphi}^K}(1-\tau^\pi), \tag{2}$$

here $w^o_{i,t}/A_i$ is the current offered wage paid for the additional labor required to produce an additional unit of output, $\bar{p}^K_{i,t}$ is the capital price in firm i's current network of suppliers (see Appendix A.3.3 for more details), which means $\bar{p}^K_{i,t}\kappa_s$ the effective capital cost the firm pays to produce an additional unit. $\tilde{\varphi}^K \in [0,1]$ is the desired capital utilization rate (0.8 in this model, as calibrated to empirical data, held equal for all agents), which is an important determinant of the firm's ability to withstand large shocks (as will be further discussed later). τ^π is the profit tax rate (held equal throughout the simulation).

Firms have a target marginal profit rate $\tilde{\pi}$, based on which they set their desired growth rate $\tilde{g}^q_{it}$ (a similar mechanism can be found in Caiani et al. (2016)):

$$\tilde{g}^q_{i,t} = \gamma^g\left(\frac{\hat{\pi}_{i,t} - \tilde{\pi}}{\tilde{\pi}}\right), \tag{3}$$

with γ^q being the sensitivity of the desired growth rate to marginal profitability. The desired production target then becomes $\tilde{q}^+_{i,t} = (1 + \tilde{g}^q_{i,t})q^+_{i,t}$, and the desired capital stock is $\widetilde{K}_{i,t} = \tilde{q}^+_{i,t}\kappa_s/\tilde{\varphi}^K$.

For the desired labor stock $\widetilde{L}_{i,t}$ the firm also takes into account whether it could not meet the demand $d_{i,t}$ for its output, computing the unmet demand $d^u_{i,t}$. CS-firms base unmet demand on true realized demand and production: $d^u_{i,t} = \min(d_{i,t} - q_{i,t}, 0)$, whereas CG- and KG-firms base this on true demand and the inventory level $I_{i,t}$: $d^u_{i,t} = \min(d_{i,t} - I_{i,t}, 0)$. When $d^u_{i,t} > 0$ the firm will hire additional workers, constituting a type of 'Keynesian' labor demand, which is particularly important after a large supply-side shock (Bils et al., 2013). Furthermore, the firm will not hire more workers than can service their current capital stock (i.e. $\widetilde{L}^+_{i,t} = K_{i,t}/(\kappa_s A_i)$), as this would mean paying wages without receiving any revenue in return. The desired labor stock is then[2]:

$$\widetilde{L}_{i,t} = \min\left(\frac{\tilde{q}^+_{i,t} + \chi^{\mathrm{Key}} d^u_{i,t}}{A_i}, \frac{K_{i,t}}{\kappa_s A_i}\right), \tag{4}$$

where $\chi^{\mathrm{Key}} \geq 0$ determines how sensitive firm's labor demand is to output demand shocks.[3] In order to react faster to shocks to the capital stock or unmet demand, $\widetilde{L}_{i,t}$ is updated every $\theta^L = 6$ periods.

So, if $\tilde{g}^q_{it} > 0$, the firm hires workers and buys additional machines, whereas if $\tilde{g}^q_{it} < 0$, the firm fires workers and lets machines depreciate without replacement. Over the next $\theta^q = 12$ months, the firm then strives to achieve this production capacity.

Meanwhile, every $\theta^p = \theta^w = 3$ months, the firm adjusts its $p_{i,t}$ and $w^o_{i,t}$ to attract enough demand and applicants to outstanding vacancies. The firm's price and wage adjustment heuristics are based on the ratio of supply-to-demand: $z^d_{i,t} = q_{i,t}/d_{i,t}$ and the ratio of the number of applicants $L^A_{i,t}$ to the number of vacancies $L^V_{i,t}$: $z^L_{i,t} = L^A_{i,t}/L^V_{i,t}$. Then, based on $z^d_{i,t}$ and $z^L_{i,t}$ the firm determines which *direction* p_{it} and w^o_{it} should be changed in. Furthermore, inventory-holding firms (i.e. CG and KG) also take into account whether their inventories $I_{i,t}$ are above or under their desired inventory level $\tilde{\iota}$. The prices are then set using the following rule[4] (with the additional condition for CG and KG-firms in square brackets):

$$p_{it} = \begin{cases} p_{i,t-\theta^p}(1+\xi^p_{i,t}) & \text{if } z^d_{i,t} < 1 \left[\text{and } I_{i,t} < \tilde{\iota}q^+_{i,t}\right], \\ p_{i,t-\theta^p}(1-\xi^p_{i,t}) & \text{if } z^d_{i,t} > 1 \left[\text{and } I_{i,t} > \tilde{\iota}q^+_{i,t}\right], \\ p_{i,t-\theta^p} & \text{else.} \end{cases} \tag{5}$$

Here $\xi^p_{i,t} \sim U\left(0, \xi^p_+\right)$ is a random uniform shock. $w^o_{i,t}$ is set every $\theta^w = 3$ periods using a similar rule, using another uniform random shock $\xi^w_{i,t} \sim U\left(0, \xi^w_+\right)$:

$$w^o_{i,t} = \begin{cases} w^o_{i,t-\theta^w}(1+\xi^w_{i,t}) & \text{if } z^L_{i,t} < 1 \text{ and hired in last } \theta^w \text{ periods,} \\ w^o_{i,t-\theta^w}(1-\xi^w_{i,t}) & \text{if } z^L_{i,t} > 1 \text{ and hired in last } \theta^w \text{ periods,} \\ w^o_{i,t-\theta^w}\omega^w + \bar{w}^o_{r,t}(1-\omega^w) & \text{else.} \end{cases} \tag{6}$$

Given that firms do not hire every period, their $z^L_{i,t}$ may not convey enough information on the current labor market conditions if the last hire was more than θ^w periods ago. In this case, firms update the offered wage to a weighted average – with weighting factor $\omega^w \in [0,1]$ – of the previous offered wage $w^o_{i,t-\theta^w}$ and the current mean offered market wage $\bar{w}^o_{r,t}$. The ω^w-parameter therefore describes how strongly firms that have not hired adapt their offered wage to the current market wage.

Therefore, through the 'fast' processes, firms stochastically search for the level of $p_{i,t}$ and $w^o_{i,t}$ that lets supply equal demand, and applicants equal vacancies, *given* a level of supply $q^+_{i,t}$. Then, after θ^q months,

[1] The updating times are distributed uniformly in the firm population. Prices, wages, and production quantities are updated based on the founding time t^*_i of the firm if $\mathrm{mod}(t^*_i, \theta) = 0$, where the founding times of the initial firms' population is uniformly distributed as $t^* \sim U(-12, 0)$.

[2] In this case, a shock to the capital stock leads to a strong drop in labor demand, resulting in rapid firing of employees. Due to (institutional) labor market frictions, such short-term firings may be infeasible certain contexts. In Section 4 we discuss extensions to incorporate such frictions.

[3] The sensitivity of the post-disaster outcomes to this Keynesian labor demand is discussed in the supplementary material.

[4] Dawid and Delli Gatti (2018) describe a range of similar rules used in macroeconomic ABMs, some of which take into account the mean market price (e.g. Delli Gatti et al., 2011; Assenza et al., 2015) or update the markup rather than the price (e.g. Caiani et al., 2016). Here, to maintain the price heterogeneity arising from the heterogeneous productivity levels and allow propagation of large-scale supply-side shocks (e.g. floods), we selected this variation based on demand, supply and inventory levels.

based on the current levels of $p_{i,t}$ and $w^o_{i,t}$ that are needed to let $d_{i,t} \approx q^+_{i,t}$, the firm can now again update $q^+_{i,t}$ using Eq. (2). All other things held equal, the firm stochastically searches for the levels of $q^+_{i,t}, p_{i,t}, w^o_{i,t}$ for which (i) the desired profit rate is reached, (ii) supply equals demand, and (iii) sufficient labor is attracted.

Apart from $q^+_{i,t}, p_{i,t}, w^o_{i,t}$, the firm also has to manage its stocks of production factors labor $L_{i,t}$ and capital goods $K_{i,t}$, and its *buffer* stocks of inventories $I_{i,t}$ and cash holdings $C_{i,t}$. Firstly, $L_{i,t}$ is managed through hiring and firing employees (the labor market matching is described in Appendix A.3.4), and $K_{i,t}$ is managed by buying capital goods from KG-firms. The firm's capital stock consists of discrete 'machine' units with Weibull-distributed breaking times, where older machines are more likely to break. Firms write off machines at their expected breaking time and order a replacement. This uneven timing of machine orders and breaking make investment 'lumpy', which is exacerbated by the endogenous coordination failures in the capital goods market (The matching process capital goods markets is described in Appendix A.3.3.) This lumpiness is observed in empirical firm investment behavior (Doms and Dunne, 1998), and introduces frictions that slow down recovery after a shock (Baley and Blanco, 2021), making them an important feature of flood shock propagation through the economy.

Secondly, the firm's buffer stocks (i.e. inventories and cash holdings) are meant to isolate it from unexpected shocks. The endogenous frictions in the non-Walrasian markets (i.e. markets typically do not fully 'clear', with remaining excess demand and supply) and continually changing market conditions mean firms will typically not be able to perfectly coordinate supply and demand. Therefore, maintaining an inventory helps avoiding unmet demand. For this same reason firms strive for a capital utilization rate below full capacity ($\tilde{\varphi}^K < 1$) such that unexpected demand surges can be more easily met with increased supply. Buffers like inventories and idle capacity 'cushion' the impact of large-scale (environmental) shocks to the whole economy, as shown by e.g. Hallegatte (2014), Otto et al. (2017) and Hallegatte et al. (2024) at the sectoral level, and are therefore crucial for modeling post-shock dynamics. Inventory-holding firms aim to have $\widetilde{I}_{i,t}$ of size $\tilde{\iota}$ times their production capacity, which they manage through the pricing rule in Eq. (5). If $I_{i,t} > \tilde{\iota} q^+_{i,t}$ the firm will decrease its production to not have excess inventories. Because CS-firms cannot hold inventories, they always produce at full capacity.

Furthermore, because firms have no access to debt or credit, they need to maintain large enough cash holdings $C_{i,t}$ to afford production expenses, investments, as well as unexpected cost increases. For this, they set a minimum amount of cash needed to maintain the current production size $C^-_{i,t} = \phi^- p_{i,t} \bar{q}^+_{i,t}$, where ϕ^- is the minimum ratio of expected revenues that the firm desires to have. If the firm has less cash holdings $C_{i,t}$ than this amount, it will reduce spending by (1) reducing additional hiring, (2) reducing investments, and (3) firing workers (but only if the firm would otherwise have negative cash holdings). The *true* demand for labor $L^d_{i,t}$ and capital $K^d_{i,t}$ will then only equal the desired quantities $\widetilde{L}_{i,t}$ and $\widetilde{K}_{i,t}$ if the firm can afford it, otherwise they are scaled down until $C^-_{i,t}$ is again achieved. The firm pays out cash holdings over $C^+_{i,t} = \phi^+ p_{i,t} \bar{q}^+_{i,t}$ as dividends, which are distributed to households through the mutual fund.

At the end of the period, if a firm can no longer afford to produce one unit of output (i.e. they cannot afford to hire a single employee, or buy the required capital goods) it is declared 'bankrupt'. Its remaining employees are fired and liquid assets returned to the mutual fund. In its place, a new firm is founded, which starts at a fraction $\varphi^{\mathrm{NF}}_{i,t} \sim U(\varphi^{\mathrm{NF}}_-, \varphi^{\mathrm{NF}}_+)$ of the mean production capacity of its sector in the region[5]: $\bar{q}^+_{i,t} = \varphi^{\mathrm{NF}}_{i,t} \bar{q}^+_{s,r,t}$. The new firm then receives a 'venture capital' injection from the mutual fund, consisting of enough cash to buy capital goods and pay wages for the coming 12 months, given its production target. The firm chooses between region r and r' based on the current mean profit rate of firms in the region:

$$\mathbb{P}(\mathrm{enter})_{i,r} = \frac{\left(\bar{\pi}_{r,t}\right)^{\gamma^{\mathrm{Entr}}}}{\left(\bar{\pi}_{r,t}\right)^{\gamma^{\mathrm{Entr}}} + \left(\bar{\pi}_{r',t}\right)^{\gamma^{\mathrm{Entr}}}} \tag{7}$$

Lastly, at the end of each period all (surviving, incumbent) firms can decide to relocate to the other region based on the expected profitability in the alternative region and the current expected profitability:

$$\mathbb{P}(\mathrm{relocate})_i = 1 - \exp\left(-\gamma^{\mathrm{MigF}} \frac{\hat{\pi}_{r',t} - \hat{\pi}_{i,t}}{\hat{\pi}_{i,t}}\right), \tag{8}$$

where the firm only considers moving if the expected profitability in the alternative region is higher than the current expected profitability ($\hat{\pi}_{r',t} > \hat{\pi}_{i,t}$). $\hat{\pi}_{r',t}$ is based on the offered wages and capital price in the alternative region. Furthermore, the chance of relocation increases with a larger divergence between $\hat{\pi}_{r',t}$ and $\hat{\pi}_{i,t}$.[6]

2.2.2. Households

Every period the household $j \in \mathcal{H}$ decides (1) how much of their income to consume and save, (2) whether to switch employers, and (3) whether to migrate to another region. All these decisions (indirectly) affect the household's nominal disposable income:

$$y_{j,t} = \begin{cases} \left(w_{j,t} + y^{\mathrm{CI}}_{j,t}\right)(1-\tau^y) + y^{\mathrm{SB}}_{j,t} & \text{if } j \text{ is employed} \\ \left(y^{\mathrm{UB}}_{j,t} + y^{\mathrm{CI}}_{j,t}\right)(1-\tau^y) + y^{\mathrm{SB}}_{j,t} & \text{if } j \text{ is unemployed,} \end{cases} \tag{9}$$

where $w_{j,t}$ is the wage paid to the household by its employer if employed, and $y^{\mathrm{UB}}_{j,t}$ the unemployment benefits paid by the government if the household is unemployed. $y^{\mathrm{SB}}_{j,t}$ are the social benefits paid out by the government, and $y^{\mathrm{CI}}_{j,t}$ is the capital income paid out by the mutual fund.

Households set their nominal consumption budget $b_{j,t}$ and savings to smooth out unexpected income shocks (due to unemployment, price hike or a flood). Their stock of liquid wealth $W_{j,t}$ evolves as:

$$W_{j,t} = W_{j,t-1} + y_{j,t} - \sum_{i \in F} d_{j,i,t} \vartheta_{j,i} p_{i,t}, \tag{10}$$

where $d_{j,i,t}$ if the demand from household j for output of firm i. Here, $\sum_{i \in F} d_{j,i,t} p_{i,t} \leq b_{j,t}$, meaning there may be involuntary saving if not all demand is met due to failed market coordination. Households first set real demand $d_{j,t}$, after which they set their consumption budget $b_{j,t}$, of which the household spends a fraction ρ^{CG} on consumer goods and a fraction $1 - \rho^{\mathrm{CG}}$ on consumer services. The household adjusts its real demand for output $d_{j,t}$ to achieve a target level of savings $\widetilde{W}_{j,t}$, where they will save a part of their income (spend part of their savings) if their savings are below (above) this target. They therefore follow a version of the buffer stock rule (Carroll, 1997), as commonly used in macroeconomic ABMs (Dawid and Delli Gatti, 2018). For this, households first determine their *permanent* income $y^P_{j,t}$ as an exponentially moving average:

$$y^P_{j,t} = y^P_{j,t-1} + \chi^P \left(y_{j,t} - y^P_{j,t-1}\right), \tag{11}$$

with $\chi^P \in [0,1]$. The wealth target is then a function of permanent income $\widetilde{W}_{j,t} = \tilde{\rho}^{\mathrm{LW}} y^P_{j,t}$, and the households smooths its real consumption budget as:

$$d_{j,t} = \frac{1}{\bar{p}_{j,t}} \left(y_{j,t} + \chi^W \left(W_{j,t-1} - \widetilde{W}_{j,t}\right)\right) \tag{12}$$

[5] Because $\varphi^{\mathrm{NF}}_+ < 1$, new firms are smaller than incumbents (as empirically observed (Bartelsman et al., 2005)). This same entrance approach is used by Dosi et al. (2010).

[6] The sensitivity of post-shock outcomes to the migration propensity γ^{MigF} of firms is further explored in the supplementary material.

where $\bar{p}_{j,t}$ is the mean consumer price for the output offered to the household (see Appendix A.3.2) and $\chi^W \in [0,1]$ determines the speed by which households adjust their consumption to the state of their liquid assets stock. The consumption budget then becomes $b_{j,t} = \bar{p}_{j,t} d_{j,t}$, where households cannot spend more than their current stock of liquid assets (i.e. cannot incur debt), but always have a minimum budget of y^{UB}, which serves as the subsistence consumption level.

After the consumption budget is set, households spend it on consumer goods and services. They do not only desire low prices, but also a variety of both goods and services. As such, the firm with the cheapest output will not simply get all the household demand, simulating a 'heterogeneity' of the goods and services without *explicitly* modeling it, as in Dixit and Stiglitz (1977). Therefore, instead of the low-productive firms being instantly outcompeted, this allows for a steady state with a variety of low- and highly-productive firms to co-exist, as is also observed empirically (Axtell, 2001; Bartelsman et al., 2005) and is crucial for our later experiments. We describe the consumer market matching in detail in Appendix A.3.2.

Households decide whether to enter the job market and to which job opening to apply. All unemployed households apply for jobs. Employed households decide to look for alternative employment with a fixed probability. When searching, the household is more likely to apply to vacancies with a higher offered wage (further discussed in Appendix A.3.4). Once the household has received a job offer, it will only accept if the offered wage $w^o_{i,t}$ is greater or equal to its reservation wage $w^r_{j,t}$, which for employed households is equal to its current wage $w_{j,t}$, and for unemployed households is equal to its last earned wage $w_{j,t'}$, reduced as its unemployment duration $T^U_{j,t}$ takes longer: $w^r_{j,t} = w_{j,t'}(1-\delta^U)^{T^U_{j,t}}$, $\delta^U \geq 0$. Because households do not have perfect information on all employers with outstanding vacancies, each single time step there might be firms and households that are not matched, leading to labor market frictions, as is further discussed in Appendix A.3.4.

Lastly, households decide whether to migrate to another region based on the offered nominal wages (indicating employment opportunity) and price levels in the other region — together forming the real offered wage. Differences in income and employment are important drivers of migration (Blanchard et al., 1992; Kennan and Walker, 2011). The probability of migrating from region r to region r' is computed as:

$$\mathbb{P}(\text{migrate})_{j,t} = 1 - \exp\left(-\gamma^{\mathrm{MigH}} \frac{w^o_{r',t}/\bar{p}_{r',t} - w^o_{r,t}/\bar{p}_{r,t}}{w^o_{r,t}/\bar{p}_{r,t}}\right) \tag{13}$$

where households will only move if $w^o_{r',t}/\bar{p}_{r',t} > w^o_{r,t}/\bar{p}_{r,t}$. While the overall probability of moving typically remains small – even if the difference in real offered wages is large – if one region has worse conditions for an extended period (e.g. after an environmental shock), this can still induce a significant number of households to move. Furthermore, as the condition in the affected region normalizes, this does not necessarily induce households to move back.[7]

2.3. Climate shock and macroeconomic dynamics

2.3.1. The climate shock

The exposed region is struck by a climate-induced shock, which we contextualize as a flood. Hence, a single flood hits our simulated economy at time $t^{shock} = 400$ (held equal across all experiments). Here, we chose t^{shock} after the economy has converged to a statistical equilibrium in the benchmark scenario (see Section 2.4). This ensures the model has stabilized after its warm-up phase, enabling us to identify the 'clean' impacts of the flood shock without being distorted by the model's initial transient dynamics. The simulated climate-induced flood represents a 'tail event' shock, meaning it is large, rare and unexpected by the agents. The flood shock directly affects firms in the exposed region in two ways: the destruction of capital and inventories, and the interruption of business operations. After the shock, firms try to replace as many of destroyed machines as they can afford (see the budgeting rules described above), which is easier for firms with either small damages or large enough cash holdings. The other three types of agents are not directly affected, but do experience indirect damages through market interactions, price adjustments, bankruptcies and migration responses. As our focus lies with distilling the pure effect of firms' heterogeneity, households in EMERGO are simplified. Our previous work has explored the effects of damages to household assets (Taberna et al., 2023a).

During the shock, a fixed fraction $\zeta^K_{\mathrm{ND}} \in [0,1]$ of the total regional stock of capital and inventories is destroyed. The ζ^K_{ND}-parameter determines the severity of the shock, which is kept fixed at 0.3 (or 30%) across all experiments (see Section 2.4). The shock affects (on average) a fraction $\zeta^F_{\mathrm{ND}} \in [0,1]$ of firms in the exposed region. This means the damage per firm $\xi^{\mathrm{ND}}_{i,t} \in [0,1]$ is on average $\mathbb{E}\left[\xi^{\mathrm{ND}}_{i,t}\right] = \zeta^K_{\mathrm{ND}}/\zeta^F_{\mathrm{ND}}$ (with $\zeta^K_{\mathrm{ND}} \leq \zeta^F_{\mathrm{ND}}$). As such, the ζ^F_{ND}-parameter determines whether the shock is concentrated with a few firms or spread out over many firms. Depending on the experimental setup (see Section 2.4), the actual per-firm damages are either the same for all firms or randomly drawn from a Beta distribution: $\xi^{\mathrm{ND}}_{i,t} \sim \mathrm{Beta}\left(\alpha^{\mathrm{ND}}, \beta^{\mathrm{ND}}\right)$.[8]

Apart from capital damages, shocked firms are also temporarily forced to halt production. Because floods often require production facilities to be dried, cleaned and potentially decontaminated (Merz et al., 2010), firms can suffer a significant loss of revenue, which has been found to be an important cause of bankruptcy (Sydnor et al., 2017). The business interruption lasts longer with higher inundation depth (for which we take $\xi^{\mathrm{ND}}_{i,t}$ as the proxy), and increases non-linearly as:

$$T^{\mathrm{close}}_{i,t} = T^{\mathrm{close}}_{+} \left(\xi^{\mathrm{ND}}_{i,t}\right)^{\gamma^{\mathrm{close}}}, \tag{14}$$

with $\gamma^{\mathrm{close}} > 1$, meaning the closing time is convex in the destroyed fraction $\xi^{\mathrm{ND}}_{i,t} \in [0,1]$. During the business interruption the firm can sell the remaining inventory that was not destroyed by the flood.

2.3.2. Macroeconomic dynamics after the climate shock

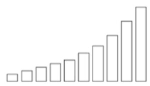
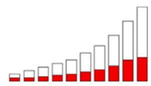
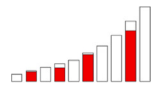
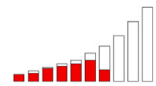
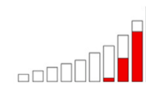
The individual losses to and adjustments of economic agents shape the aggregate post-flood economic dynamics. Much of the initial damages are attenuated using the buffers agents hold: cash reserves, inventories and idle machines for firms, savings for households. In EMERGO, the size of buffers held by firms and households is based on empirical estimates of inventories, capital utilization and household savings. While such buffers enable the economy's to absorb (much of) a destructive shock and recover quickly (Hallegatte, 2014), they are no longer sufficient if the shock is large enough. The latter forces many firms to close down (temporarily or permanently), many households to lose employment, and the economy to remain outside of its full-employment and production steady state for an extended period. Due to endogenous frictions on the output and labor markets, prices and wages do not 'jump' to their new clearing level, and output can remain below its full capacity level for an extended period, also affecting agents that are not directly shocked.

As these search frictions are resolved, the decentralized market mechanisms modeled in EMERGO shape the economy's path to its (new) steady state. Firstly, the post-flood supply drop increases the

[7] The supplementary material contains the sensitivity analysis of both the γ^{MigF}-parameter and the γ^{MigH}-parameter. This shows that the firm's and household's propensity to move to the other region is an important cause for hysteresis effects — where short-term direct impacts translate into long-term effects (Cerra et al., 2023). There, we also provide additional discussion.

[8] Similar granular firm-level shocks are employed by e.g. Lamperti et al. (2018, 2019) and Taberna et al. (2022).

Table 1
Overview of the parameters that form our five experimental setups. Parameter that are not directly set but implicit are shown in cursive. For Setup III this is the mean damage, as this depends on the fraction of affected firms, and the fraction of the total regional capital stock that is destroyed. For Setup IV and V, the fraction of firms affected depends on whether selection by productivity is low-to-high or high-to-low. Apart from the parameters described above, no other parameters are changed between the Setups.

Experimental setup:	I: Benchmark	II: Uniform & Spread-out	III: Heterogeneous & Concentrated	IV: Low-to-high	V: High-to-low
					
Has flood	No	Yes	Yes	Yes	Yes
Fraction of totalcapital and inventories destroyed (ξ^F_{ND})	0%	30%	30%	30%	30%
Fraction of firms affected (ζ^F_{ND}) to meet the same 'fraction destroyed' in II–V	0%	100%	40%	*~68% (least productive firms)*	*~17% (most productive firms)*
Determination of firm-level damages	–	Deterministic (all damaged the same)	Random (drawn from Beta distribution)	Random (drawn from Beta distribution)	Random (drawn from Beta distribution)
Mean damage to an affected firm to ensure 30% aggregate damage	0%	30% (deterministic)	*75%*	75%	75%
Productivity of affected firms	–	All firms	Randomly selected	Low-to-high productivity	High-to-low productivity

demand-output-ratio for firms, causing a price hike. At the same time, firms may go bankrupt or fire excess workers after their capital is destroyed, leading to an increasing supply of labor and a subsequent drop in wages. The decreased capital stock, increased output price and decreased wages increase the marginal value of investing in capital goods. This leads to a surge in investments that brings the economy back to its pre-shock steady state. As such, firms incorporate both supply- and demand-side effects of shocks in their behavior, leading to recovery on the aggregate level. However, as this process takes longer, more households and firms may decide to move to the safe region, and the struck economy can be persistently scarred.

2.4. Design of experiments

To study the impact of firm heterogeneity on post-flood economic dynamics, we define five experimental setups, which we will refer to as Setups I to V. An overview of all Setups is given in Table 1. Setups I and II show the model dynamics, firstly in the no-flood case (Setup I, our benchmark counterfactual), and secondly in a 'shallow and uniform' flood scenario (Setup II) where we assume all firms in the exposed region have the same fraction of machines and inventory destroyed. Setups III, IV and V then show how the economy-wide dynamics change when the distribution of firm-level impacts of a climate shock changes aligned with our research questions. The flood shock in Setups II–V always destroys 30% of the total machine and inventory stocks in the exposed region. Furthermore, each of the five Setups is run 100 times using 100 stochastic seeds. The same 100 seeds are used across all five setups, meaning that, for each random seed, the Setups I to V are *exact* copies until the moment of the shock, and any difference between Setups I and V are fully attributable to the flood shock and its distribution across the firms.

In Setup I: *Benchmark* we study the behavior of the economy when no flood shock occurs. This serves as the benchmark to which we compare the other experiments. In Setup II we shock the exposed regions with a *Uniform & Spread-out* flood. Here, the shock destroys an identical fraction of capital and inventory of all shocked firms (i.e. uniform), and all firms in the exposed region are shocked (i.e. spread-out). So, as the flood affects 100% of firms, each firm loses 30% of the machine and inventory stock. This setup represents the aggregated 'sectoral' view where no distinction in damages is made between individual firms, as is commonly employed in macro-economic modeling frameworks.

We answer RQ1 – whether distributing those 30% total damages differently over the firm population affects the aggregate outcomes – by comparing 'Setup III: *Heterogeneous & Concentrated*' to the conventional shock in Setup II. In Setup III, a smaller subset of the firm population, simulating a shock to a cluster of spatially concentrated firms. Here, only 40% of the exposed firm population is actually shocked. While the individual damages per firm are heterogeneous and drawn from a Beta distribution, these damages will on average be 75% of the capital and inventory stock, as this is required to reach the 30% of total destruction when only 40% of firms are shocked.

Lastly, we answer RQ2 – whether aggregate outcomes change when more or less productive are more prone to be shocked – using Setup IV and V. These Setups enable us to mimic the real-world patterns when either the least productive firms are priced into hazard-prone areas (Setup IV), or when economic clusters agglomerate next to the waterways due to the competitive advantage of those locations (Setup V). For this, the hazard either affects only the least productive (Setup IV: *Low-to-high*) or the most productive firms (Setup V: *High-to-low*). The firm population is sorted either low-to-high or high-to-low productivity, and then shocked until a total of 30% of machines and inventories in the exposed region is destroyed. Again, the damages per firm are heterogeneous and drawn form a Beta distribution, but the average damage per firm is 75% (as in Setup III). Because firm size depends on the productivity level, this means that the fraction of firms destroyed now depends on the order of sorting. When sorting high-to-low, we shock big firms first, reaching the 30% regional losses cap when only 17% (on average) of firms are affected. Conversely, when sorting low-to-high, we need to shock nearly 68% (on average) of firms to reach 30% of total regional damages.

3. Results

While our model traces time-series data at the agent level, here, guided by our research questions, we report regional-scale aggregate dynamics. Specifically, we focus on the macroeconomic indicators — Real GDP, household population size, unemployment rate, mean real wages, average consumer prices and capital good prices across bilateral transactions, average firm productivity across heterogeneous firms, and firm post-shock survival rates. We report each indicator separately for the safe and exposed regions as means and standard deviations across the 100 random seed runs for each experiment. Since these macroeconomic dynamics emerge from the micro-level economic interactions

Panel 1: Simulation results of shock to exposed region on aggregate variables in exposed and safe regions

Panel 2: Schematic overview of a shock transmission in the exposed region

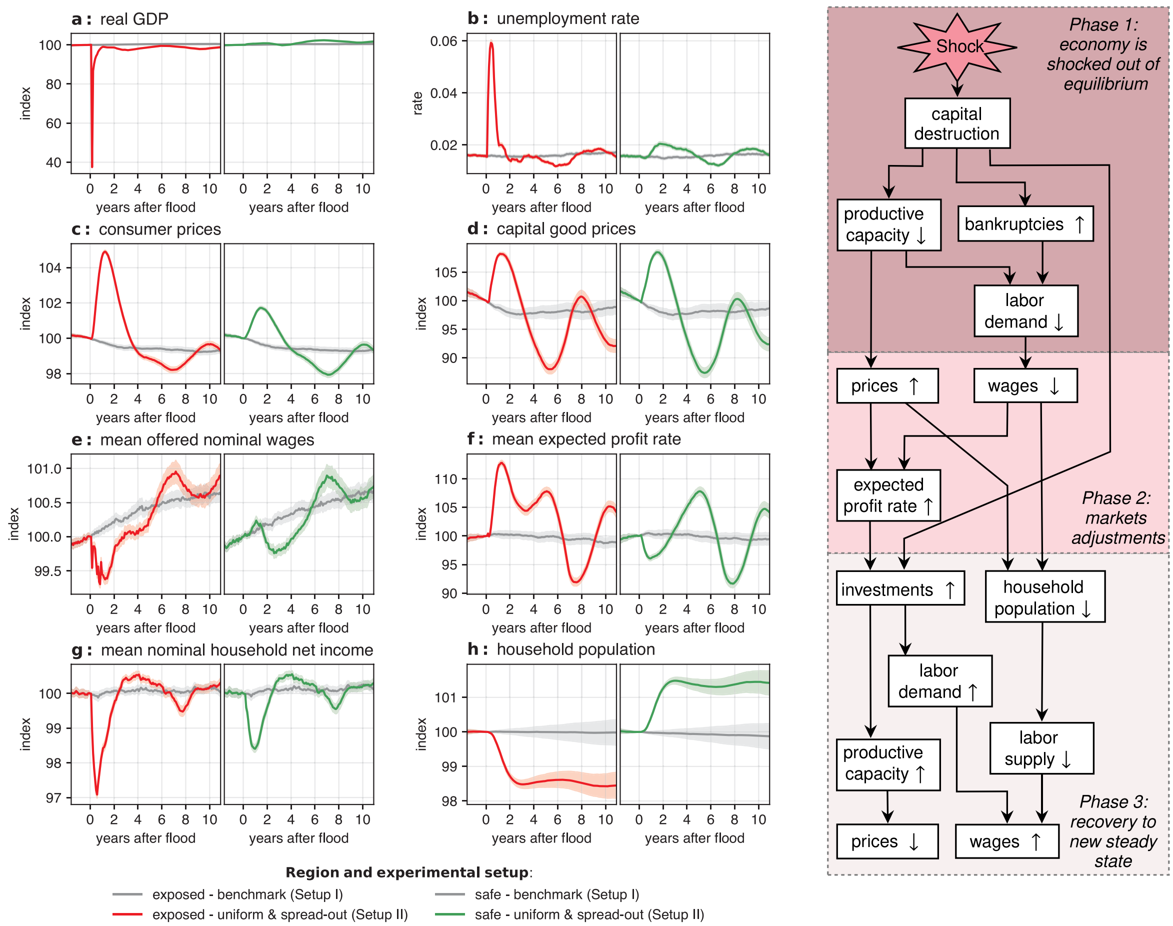


Fig. 2. Aggregate macro dynamics illustrating the performance of the two-region economy in the no-shock (Setup I, gray curves) and shock cases (Setup II, with red curves for the exposed and green curves for the safe region). Panels (1).a–(1).h present the EMERGO model outputs for the period of 10 years after the shock. Here, all curves show the mean values across 100 Monte Carlo runs, the shading represents the 95% confidence interval for the mean value. All graphs in Panel (1), except Panel (1).c, show the mean of the indexed value, where the month before the shock is the index ($t^{\mathrm{ND}}-1 = 100$). Panel (1).c shows the actual mean value for the unemployment rate. Panel (2) illustrates the corresponding phases of economic adjustments after an environmental shock, clarifying specific mechanisms of change. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

in EMERGO, we can trace back all changes in trends to the specific economic mechanisms, which we discuss below.

3.1. Floods and macroeconomic recovery dynamics

To set the benchmark on how an economy reacts to a hazard shock in the EMERGO ABM, we compare the no-shock benchmark (Setup I) with the uniform and spread-out flood shock (Setup II). In the absence of a climate shock, the economy displays stable dynamics, with GDP, population, employment, prices, and wages being largely stable over the 10-year period (see Fig. 2 Panel (1), gray curves for Setup I). However, when a climate-induced shock does hit, capital destruction and business interruption have a big impact on real GDP in the exposed region. Since EMERGO explicitly traces out-of-equilibrium dynamics, we can observe how the shock transmits throughout the economy, aligning macrodynamic along different recovery phases shaped by various micro-level mechanisms (Fig. 2 Panel (2)). We distinguish three phases in the economy adjustments to environmental shocks: (1) a shock event and immediate direct damages to firms' assets, (2) the short-run indirect effects, (3) the long-run (4+ years) indirect effects.

In Phase 1, the model is shocked out of its previous steady state. In the month of the flood, output drops by more than 50% in the exposed region. However, output quickly rebounds the months after (Fig. 2 Panel (1).a, red curve for year 0–1), which shows how the cash reserves, inventories and idle machines held by firms form a buffer that mitigates most of the immediate damages in the short run. This recovery seems *very* quick, and is only possible in the (unrealistic) scenario where all firms in a region bear *exactly* the same share of damages. Because firms will have a capital utilization level close to 80% in the pre-shock steady state (see Section 2.2.1), this means 30% destruction only leads to an *effective* loss of 10% of the production capacity, which through the inventories of KG-firms can be relatively quickly recovered.[9] Therefore, while Setup II approximates the capital destruction in a fully aggregated modeling type, it is not representative

[9] In the supplementary material we zoom in further on the period immediately following the shock, showing how the firm-level buffers cushion the macro-level shock. Here, the sensitivity results for the target capital utilization rate $\tilde{\varphi}^K$ can also be found, which show the economy is more heavily affected in Setup II when $\tilde{\varphi}^K$ is closer to one (i.e. less idle capacity). This shows the importance of idle production capacity for cushioning the shock impact.

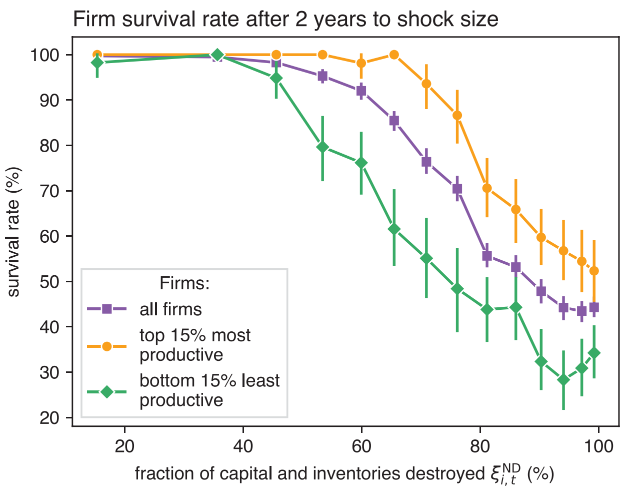


Fig. 3. Firms' mean survival rates 2 years after the shock for flooded firms estimated based on the firm-level results of Setup III. Survival rates are plotted against the extent of damage (fraction of machines and inventories destroyed, ξ_{it}^{ND}), and shown for the full sample of firms (purple), the 15% most productive (orange) and 15% least productive (green) firms in the sample. Curves indicate the mean survival rates of firms over the 100 simulations, and the bars indicate the 95% confidence interval for the mean survival rate in within the bin for the 100 simulations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

of a real-world shock. However, despite the strong effects of the buffers, output does not immediately recover its full pre-shock level in the month after the flood, as the buffers are not sufficient to fully absorb the shock. Some firms go bankrupt, whereas others cannot acquire or afford replacement capital, leading to firing households and unemployment increase (Fig. 2 Panel (1).b, red curve for year 0–1). The economy has now moved away from its 'full employment' output level.

In Phase 2, because of the sudden drop in overall production capacity in the exposed region, firms and households shift their demand to intact firms in both regions. As these firms now face excess demand, they start increasing their individual prices, causing to a sharp rise in the overall market price levels in both regions (Fig. 2 Panels (1).c,d, years 0–2 in red and green curves). The wave of firings increases the labor supply, which leads to a large increase in the number of applicants per vacancy. This induces firms in the exposed region to decrease the offered wage (Fig. 2 Panel (1).e, red curve for years 0–2). This is not yet met with an increase in labor demand from unaffected and recovering firms, because production targets are set more slowly than pricing and wage decisions (see Section 2.2.1), leading wages to decrease in the short run (which is also observed empirically (Groen et al., 2020)). However, the reaction of wages is weakened due to labor market frictions: unemployed households do not immediately bring down their reservation wages, inhibiting wages to quickly clear the labor market. Nevertheless, the heightened price levels and lowered offered wages lead to an increase in the expected profit rate in the exposed region (Fig. 2 Panel (1).f, red curve for years 0–1). This provides the incentive for firms in the exposed region to invest in recovery.

In Phase 3 (from year 4 onward), agents adjust their behavior to the new price and wage levels. The high unemployment rate and the drop in capital income and wages lead to a large drop in household disposable income (Fig. 2 Panel(1).g, red curve years 0–2), further exacerbated in real terms by the price hike. As the cut in disposable real income is not as big in the safe region (Fig. 2 Panels (1)c,g, green curves years 0–2), this induces a portion of the households in the exposed region to move to the safe region (Fig. 2 Panel (1).h, red and green curves years 0–2). This population shift is small (only around 2%), as the unemployment rate and offered wages recovery quickly back to the previous trend. The heightened expected profit rate has induced investments that enabled a quick recovery, and the economy already performs close to its counterfactual output level within a year, despite the large damages. These results show that aggregate impacts of the uniform and shallow shock are limited, as suggested by part of the empirical and modeling literature. Furthermore, these results illustrate how the ABM allows to trace the economy being shocked out of its steady behavior, after which the ('fast') pricing mechanisms and ('slow') investments bring the economy back to its initial output level in our Setup II.

3.2. Flood impacts at the firm-level

Next, we study how flood damage affects the chance of surviving the shock impact for individual firms. We report firm-level simulated data from the heterogeneous & concentrated shock (Setup III), which allows to study overall survival probabilities (Fig. 3), as well as how they relate to firm-level heterogeneities. Here, we find that the survival probability of individual firms depends on (1) how severely it was damaged, and (2) on its pre-shock productivity level.

Firstly, firms with more severe damages have a lower chance of survival. This impact is nonlinear — the survival rate remains close to 100% when less than 50% of machines and inventories are destroyed, but it quickly decreases thereafter. Empirical studies using firm-level data have revealed similar high impacts of damage severity on survival probability (Sydnor et al., 2017; Basker and Miranda, 2018; Fatica et al., 2024; Cole et al., 2019), but did not estimate aggregate implications. In Setup III, the damage distribution is left-skewed (see Fig. B.8.f), which means that while most firms are unaffected, the firms that are affected incur heavy damages , while in Setup II all firms are damaged, but they receive milder damages. As firm bankruptcies increase nonlinearly and overall damages are kept the same, this indicates a more concentrated shock would increase bankruptcies, which could have significant impacts on output and employment. In Section 3.3 we examine what effect this has on aggregate dynamics.

Secondly, the firm-level data from EMERGO also show that the productivity level of the firm matters for the survival probability, but only for shocks that destroy more than 50% of machines and inventories (Fig. 3, green and orange curves). Here, the top 15% most productive firms always have a significantly higher survival rate than the full firm population, whereas the bottom 15% always have a significantly lower survival rate. The difference in survival rate between the top and bottom 15% is up to 40 percentage point for a shock of the same magnitude. The productivity level – and therefore size – of the firm is therefore an important predictor for its survival change when struck by a hazard, which is also found empirically (Basker and Miranda, 2018; Clò et al., 2024). This matters for the overall economic effects of environmental shocks, with potentially opposite implications. On the one hand, more productive firms employ more households and produce more, so *if* they go bankrupt, they cause a much bigger effect on employment and output, and hence indirect damages. On the other hand, less productive firms employ more households *per machine unit* (see Fig. B.8 in Appendix B). This means that a machine destroyed in a low-productive firm has a bigger impact on employment than if it is destroyed in a high-productive firm. Because lesser productive firms are far more numerous (Fig. B.8.e), this could therefore form a vulnerability for aggregate employment when flooded. Furthermore, as the survival rate of top-15% firms drops quickly for shocks of over 75% destruction, even concentrated shocks to clusters populated by high-productivity firms could have large impacts — despite these firms being more robust.

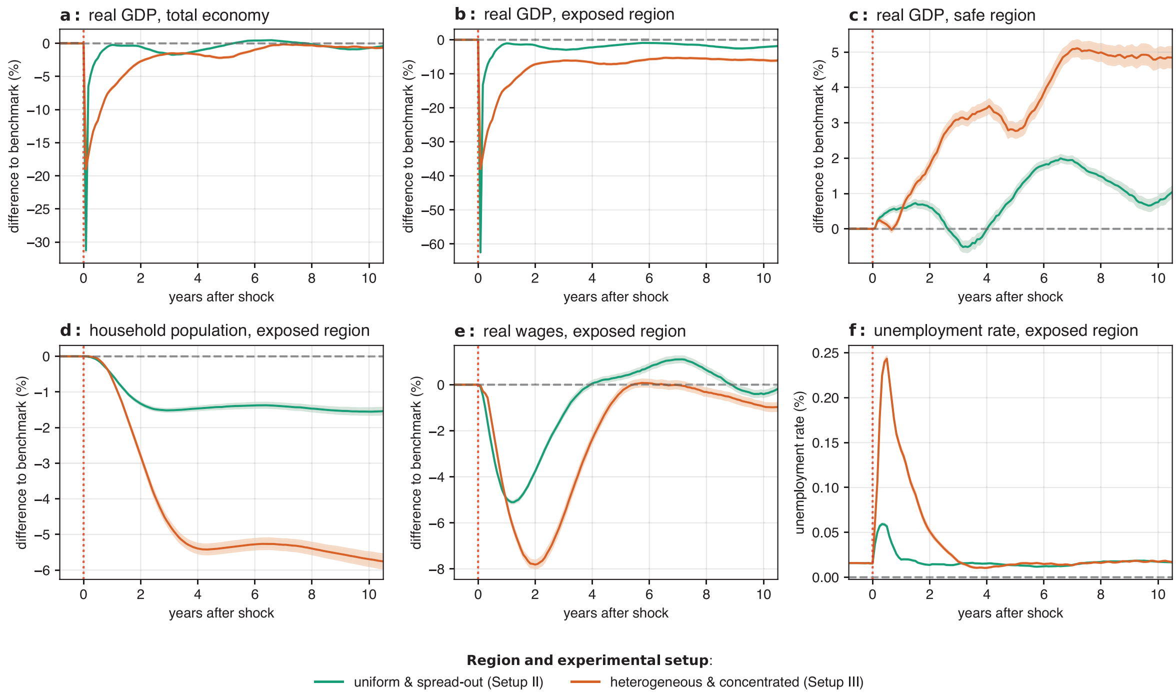


Fig. 4. The distribution of impacts is the *uniform & spread-out* (100% of firms are affected uniformly, Setup II) or *heterogeneous & concentrated* (40% of firms affected with a different degree of losses, Setup III). Curves in subplots **a–e** indicate how the mean percentual deviation over the 100 seeds from the no-shock baseline (Setup I), and curves in subplot **f** show the mean value over the 100 simulations. Shading indicates the 95% confidence interval for each of the mean values, depicting the timeline 10 years after the shock. We elaborate on how the average response is computed in the supplementary material. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.3. The effect of concentrated and shallow shocks

To address our RQ1, we compare macroeconomic dynamics emerging from micro interactions when the effects of a shock are spread uniformly over many firms (Setup II, green curves in Fig. 4) vs. concentrated with a few firms (Setup III, orange curves in Fig. 4), while keeping the overall damages the same. Since severe firm-level damages have a big impact on survival (Fig. 3), a more concentrated shock could lead to a higher number of bankruptcies. The results of Setup III confirm this, demonstrating that these micro-level heterogeneities have significant impacts on aggregate macro-dynamics (Fig. 4, orange curves). Firstly, the impact of the concentrated shock is bigger for the entire two-region economy and the exposed region in particular (compare Fig. 4.a and .b). The shallow shock of Setup II does more immediate damage (62% GDP loss in the exposed region, 31% loss overall at the time of the shock) than the concentrated shock of Setup III (38% GDP loss in the exposed region, 19% overall at the time of the shock) because it affects all firms (compare Fig. 4, green vs. orange curves). However, the shallow losses are recovered much more quickly, whereas the concentrated losses are more persistent (GDP rebounds to a loss after one year of 62% to 1% for shallow, versus 34% to 13% for concentrated). Concentrated damages therefore lead to a longer recovery path than the fully uniform shock. Inventories and idle capital capacity are also far less effective for firms that incurred damages far exceeding these buffers[10] which also translates into persistent long-term effects. Given that the damages from real-world shocks are not evenly borne by all firms but disproportionately affect a subset of firms, the recovery in Setup III provides a more realistic representation the recovery duration.

The labor market is an important determinant for these long-term effects. For the uniform shock, the swift recovery of unemployment (Fig. 4.f) and GDP (Fig. 4b) and only a small amount of households migrate (Fig. 4d). Due to the strong recovery and the (weak) migration response, this even leads to temporary wage growth after 3 years, which further discourages households to migrate. On the other hand, in the case of the concentrated shock, the high amount of firing and bankruptcies (Fig. 3) lead to a much larger overall disruption for the two-region economy compared to the conventionally assumed uniform shock (Fig. 4.a, orange vs. green curves). This creates a much larger and more persistent unemployment spike (Fig. 4.f, orange curves), resulting in a much larger drop in real wages (Fig. 4.e, orange curves). As this depression lasts longer, more households are induced to move to the safe region, triggering a population decline of around 5.7% in the exposed region (Fig. 4.d) after 10 years.[11] This number is comparable to the empirically-reported population decline in affected counties after hurricane Katrina and Rita (6.8% decline, as found by Groen et al. (2020)), and in line with broader evidence on the effect of natural disaster shocks on migration (Berlemann and Steinhardt, 2017). This migration response causes around 4.9% of GDP to be persistently substituted from the exposed region to the safe region (Fig. 4.c, orange curve), meaning the exposed region does not fully recover but settles in a lower output steady state (Fig. 4.b, orange curve). Such substitution to non-affected regions have also been found empirically (Xiao and

[10] Our sensitivity analysis shows that smaller capital buffers $\bar{\varphi}^K$ can vastly increase the effect of the uniform Setup II-shock, whereas larger capital buffers can almost fully mitigate the impacts. However, we also show that this does not hold to the same extent for the unequally distributed Setup III-shock. This shows that, while idle capacity has an important 'cushioning' effect on the shock, this effects is reduced if the shock is unequally distributed.

[11] The sensitivity results in the supplementary material show that the GDP decrease is vastly increased when firm's and agent's sensitivity to move are higher, emphasizing the importance of the labor market-migration interaction for long-term effects.

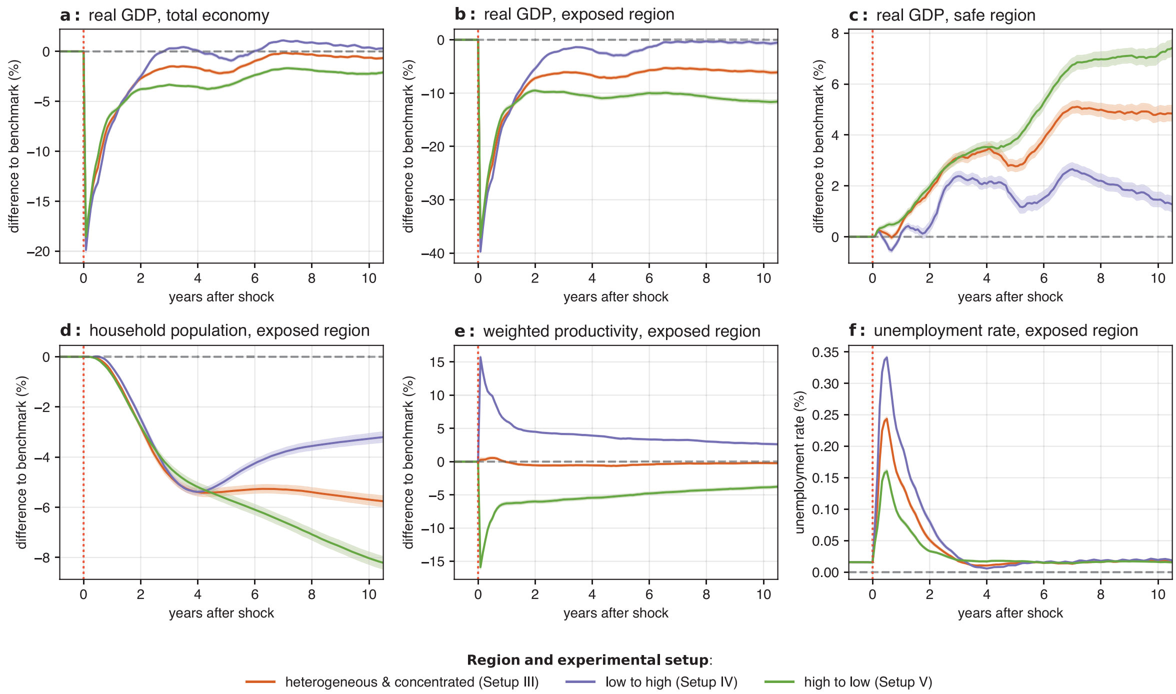


Fig. 5. Average response to flood in Setups *low to high* (Setup IV) and *high to low* (Setup V), and the *concentrated & heterogeneous* shock (Setup III) for comparison, for the 10 years after the shock. Weighted productivity (panel **e**) is computed as the average output weighted by its share of output produced using this productivity level. Curves in subplots **a–e** indicate the mean percentual deviation over the 100 seeds from the no-shock baseline (Exp-I), and curves in subplot **f** show the mean value over the 100 simulations. Shading indicates the 95% confidence interval for the mean value. We elaborate on how the average response is computed in the supplementary material. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Nilawar, 2013). These results show that concentrating damages with a few firms scar the exposed economy. In our analysis, the loss of output after 10 years in the exposed region is 2% in Setup II, and 7.3% in Setup III. This shows that assuming damages are distributed uniformly over the whole firm population, while they are concentrated with a few firms, can lead to a significant underestimation of aggregate impacts.

3.4. The effect of selection by size

Lastly, to answer RQ2, we perform a concentrated shock similar to Setup III, but vary which firms – the least productive or the most productive – take the largest hit. The results clearly show that shocking more productive firms (high-to-low) leads to much bigger aggregate impacts than selecting less productive firms (low-to-high, see Fig. 5, green vs. purple curves), and much bigger impacts than the shock in Setup III (Fig. 5, orange curve).

The outsized impact of shocking high-productivity firms can firstly be seen for the total economy (Fig. 5.a), which on average does not recover even 10 years after the hazard. This means that the damages to the exposed region are so devastating (Fig. 5.b) that they cannot be substituted even by the growth of activity in the safe region (Fig. 5.c,d). Shocking highly productive firms (Setup V) more than doubles GDP losses after 10 years in the exposed region from 6.8% to 16%, compared to Setup III. These catastrophic losses in Setup V are much larger than Setups I–IV, even though in all cases the hazard shock imposed the same total direct damage of 30% to the capital and inventories. Note that this holds despite the facts that (i) a much smaller number of firms are shocked (17% on average in high-to-low vs. 68% in low-to-high), and (ii) highly productive firms are more likely to survive a severe flood shock Fig. 3.b.

The results also show that the economy is robust against a severe shock to the least productive firms (low-to-high), even if the expected damage is 75% and 70% of the total firm population is shocked. Despite such mass destruction of small firms, the total macroeconomy even recovers faster than in Setup III (Fig. 5.a, purple vs. orange curves), and the exposed region also recovers quickly (Fig. 5.b, purple curve), even showing a slight increase in output. As expected based on the microeconomic mechanisms (Section 3.3), shocking less productive firms does cause a bigger immediate drop in employment than shocking more productive firms (Fig. 5.e, purple curve), but this drop is already less than the high-to-low case 4 years after the shock.

Both results can be explained through the change in the weighted productivity (Fig. 5.f). This shows the average productivity in the firm population, weighted by how much each much output each firm generates. In Setup III, the shock leads to relatively small decrease in productivity of the entire firms' population (Fig. 5.f, orange curve). However, if we select firms by productivity level, the shock has a much bigger impact on weighted productivity (Fig. 5.f, purple and green curves). In high-to-low (Setup V), the output of highly productive firms that go bankrupt is substituted by new and existing firms that both likely have lower productivity levels. This causes a drop in productivity for the whole two-region economy, with a subsequent drop in output (Fig. 5.a,b, green curve). In contrast, in Setup IV, lost output is substituted by more productive firms, leading to an upwards jump in productivity and a much faster recovery of GDP post-hazard (Fig. 5.a,b, purple curve).

These results extend the conclusions drawn in Section 3.3: not only are persistent economic impacts caused by the rate of bankruptcies, but also by *which* type of firm goes bankrupt. We build further on these results by testing the impact of selecting by two other potentially relevant forms of heterogeneity: financial fragility and capital intensity. For this, we have conducted additional experiments, presented in Appendix B.2. These results show how concentrating damages with *lesser* capital-intensive firms has a larger short-term impact, as these firms have a higher output-per-capital ratio. Shocking financially fragile firms leads to higher bankruptcy rates, and consequently a larger short-term drop in output. These short-term impacts (after 1 year) are often *larger* than the shocks by productivity (presented above), suggesting the shock exposure of capital ex/intensive and financially fragile firms can also importantly affect the impact of shocks. However, the results in Appendix B.2 also show that selecting for capital intensity and financial fragility has a smaller impact on long-term scarring (after 10 years) than shocking highly productive firms. This is because the destroyed capital and bankrupt financially fragile firms are easier to replace in the long run, limiting long-term impacts. These results further emphasize how assuming uniformly distributed damages over the firm population can lead to a significant underestimation of aggregate impacts — but also how long-term scarring may emerge from the fact that highly productive firms are hard to replace.

4. Conclusion

Economic analysis of (climate-induced) damages has progressed significantly over the past decades. However, much of it still analyzes the direct and indirect damages at the aggregated level of countries, regions or sectors. This leads to the implicit model assumptions that all firms are hit similarly by an environmental shock, and that recovery dynamics are not significantly affected by how losses are distributed among firms. At the same time, we observe that, when hit by disasters, some economies decline, while others either smoothly recover back or even thrive. This article strives to explore whether the way damages are distributed affects this aggregated economic dynamics. Specifically, we address two research questions: how are aggregate outcomes affected by (1) the degree of concentration of damages across firms, and (2) the extent to which less or more productive firms are more likely to be shocked. To this end, we methodologically advance the frontier of economic analysis by employing a computational agent-based economic model, EMERGO, that enables to complement the traditional macroeconomic analysis with a fine disaggregated analysis of the distributional effects. In doing so, this research makes two distinct contributions to the literature. Firstly, we show that severely damaging a few firms has a much bigger effect than damaging many or all firms moderately. Severe damages, and the bankruptcies that result from them, cause adverse indirect effects which take a much longer period to recover from than a uniformly distributed shock. As this recovery period lasts longer, the chance of persistent scarring increases, further extending the impacts of the hazard. Secondly, we show that these persistent effects are heavily exacerbated if the shocked firms are highly productive. While these firms are more robust to shocks, *if* they go bankrupt, they can cause a long-lasting decrease in productivity, and with it regional and even national output. These results show that agent-level heterogeneities can significantly impact aggregate outcomes — despite aggregate initial direct damages being the same. Therefore, our results illustrate how the economic analysis of the impact of natural disasters on the economy can be enhanced by including granular micro-level impacts (both in structural modeling (Farmer et al., 2015) and in empirical studies (Fatica et al., 2024)). This helps explain why some shocks take much longer to recover from than modeling outcomes may predict, and why some economies thrive after a shock, whereas others are persistently scarred.

Besides the methodological contribution, our results have important implications for policy. A climate-induced shock affecting the economic core (rather than a periphery) of a region can have very large and persistent impacts *beyond* the initial damages. As this core typically harbors the region's most productive firms, such clusters may become 'too big to fail', with shocks creating persistent losses in output. Furthermore, floods that cause many bankruptcies are more disruptive and take longer to recover from, especially when highly productive firms are more likely to be damaged. Long recovery times can convert to persistent losses for the affected region as they induce more households and firms to move to the safe region, which shows the importance of the speed of recoveries (as also argued by Hallegatte and Vogt-Schilb (2019)). These insights can aid in explaining the empirically observed persistence of disaster shocks (Hsiang and Jina, 2014), and how such persistence can be reduced through disaster preparedness and vulnerability reduction. Pro-active exposure reduction is therefore crucial, especially for activities and firms that are critical for a region's economy. This can be achieved by discouraging further development in risky areas, or through planned relocation of existing development (Haasnoot et al., 2021).

This paper also serves to introduce the EMERGO model. This model allows to trace how micro-level impacts propagate through various markets to macro-level effects. Through model extensions, this analysis can be deepened in various ways. At the agent-level, we focus on heterogeneous productivity levels, but other heterogeneities may be relevant, such as the size of buffers. Furthermore, the representation of households can be expanded with direct damages, demographic and financial factors, preferences and occupational specialization. Another important addition is (short- and long-term) debt, as these play an important role in recovery for both firms and households (Basker and Miranda, 2018; Zhou and Botzen, 2021; Gallagher and Hartley, 2017). The agents' behaviors can also be enriched, as they do not yet show 'agency' where they actively try to mitigate the flood-induced disruption. For instance, agents could learn to anticipate the risk of flooding and take adaptation actions. For this, the model should be extended with adaptation measures such as insurance policies or structural protection, and versatile modeling of expectations, beyond just rational, backward-looking or simply myopic. It is also important to incorporate government policies, such as disaster loans and emergency relief — which have been shown to be crucial for swift disaster recovery (Noy and Nualsri, 2011; Gallagher et al., 2023; Deryugina, 2017). In the longer run, the government could invest in protective investments or subsidize private adaptation uptake. This also allows to capture how government policies may interact with private adaptation action (e.g. through the safe development paradox (Haer et al., 2020; Taberna et al., 2022) and charity hazard (Raschky and Weck-Hannemann, 2007; Andor et al., 2020)) and to study the feedback between increasing climatic risk and fiscal stability (Agarwala et al., 2021).

Other extensions can also provide additional insight at macro-level effects. Firstly, our model is calibrated to represented an industrialized economy archetype and is validated against several empirical facts. This was done to highlight 'generic' transmission mechanisms in the post-shock economy. The validity of these mechanisms can be further enhanced by including more empirical content. For instance, future work could aim to concretize our results by validating against case studies, representing specific locations or diverse archetypes of at-risk locations. Secondly, the labor market is an important channel for (long-term) shock impacts, but is currently modeled in a very 'flexible' way. The realism of this channel can be enhanced by adding (country-specific) institutional and matching frictions, such as collectively bargained wages and employment regulations. Lastly, other important economic sectors could be included, such as construction, logistics and the financial sector. The latter would allow studying the aforementioned impact of credit and debt availability to firm and household recovery, but also systemic impacts such as financial stability after a large shock (Monasterolo, 2020; Dafermos et al., 2018; Mandel et al., 2021; Lamperti et al., 2021) and how this affects fiscal stability (Lamperti et al., 2019). Further discussion on the modeling choices and limitations can be found in the supplementary material.

CRediT authorship contribution statement

Joos Akkerman: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Servaas Storm:** Writing – review & editing, Supervision, Conceptualization. **Tatiana Filatova:** Writing – review

& editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Additional model description

A.1. Model steps

See Figs. A.6 and A.7.

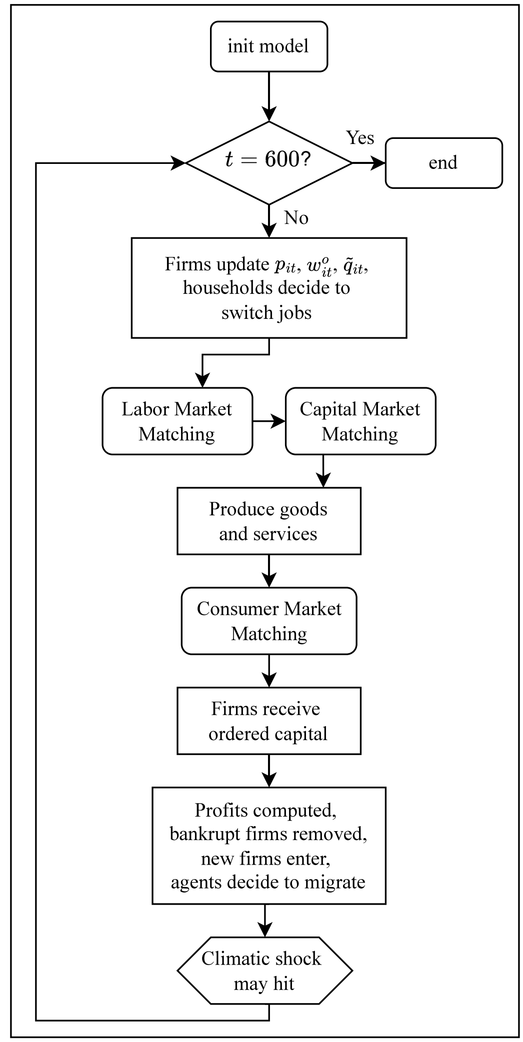

Fig. A.6. Flow diagram of the timeline of events in the EMERGO model.

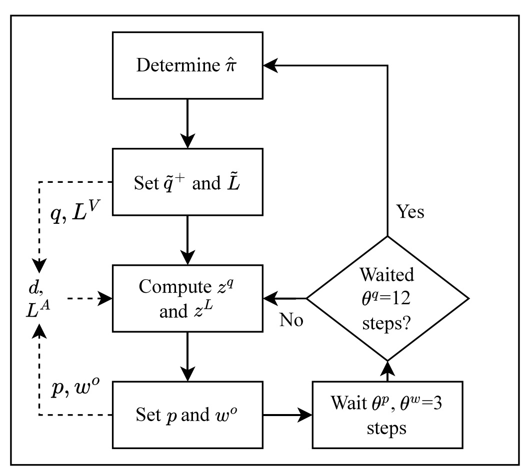

Fig. A.7. Flow diagram of firm decisions. Solid lines indicate the firm decision path, dashed lines indicate how firm decision variables interact with output and labor markets.

A.2. Institutional agents

The two institutional agents – the government and the mutual fund – exhibit simple behavior in this version of EMERGO. The stock-flow-consistency of this version of EMERGO entails that the money supply is fixed (except for deficit spending, but this money leaves the system once debts are paid off.) This means excessive accumulation of money with firms or the government can lead to monetary deflation, which results in significant real effects. In order to avoid this and keep money in circulation, excess tax revenue is spent as social benefits and excess cash of firms is paid out as capital income to households. As such, in this version of EMERGO the government and mutual fund mainly serve to retain this stock-flow-consistency. Section 4 discusses how the government's behaviors may be extended to capture disaster-related interventions.

A.2.1. Government

The government taxes household income at a flat rate τ^y and profits at a flat rate τ^π, where τ^y and τ^π are exogenously set to 10% and held stable throughout the simulation. From the total tax proceeds R^τ_t, the government pays unemployment benefits y^{UB} to unemployed households (with total sum C^{UB}_t), and social benefits y^{SB}_t to all households (with total sum C^{SB}_t). The dynamic evolution of the governmental debt D^{Gov}_t is then: $D^{\mathrm{Gov}}_t = D^{\mathrm{Gov}}_{t-1} + R^\tau_t - C^{\mathrm{UB}}_t - C^{\mathrm{SB}}_t$.

While the government can temporarily run budget deficits, it will aim for a debt-to-GDP ratio $\bar{\rho}^{\mathrm{GD}}$ of 0.5, or 50%. For this, it adapts the level of social benefits spending per household y^{SB}_t using the following rule:

$$y^{\mathrm{SB}}_t = \begin{cases} y^{\mathrm{SB}}_{t-1}(1+\xi^{\mathrm{SB}}_t) & \text{if } D^{\mathrm{Gov}}_{t-1} > -\bar{\rho}^{\mathrm{GD}} Y_{t-1} \text{ and } R^\tau_t > C^{\mathrm{UB}}_t + C^{\mathrm{SB}}_t, \\ y^{\mathrm{SB}}_{t-1}(1-\xi^{\mathrm{SB}}_t) & \text{if } D^{\mathrm{Gov}}_{t-1} < -\bar{\rho}^{\mathrm{GD}} Y_{t-1} \text{ and } R^\tau_t < C^{\mathrm{UB}}_t + C^{\mathrm{SB}}_t, \\ y^{\mathrm{SB}}_{t-1} & \text{else.} \end{cases} \tag{A.1}$$

where Y_t is the nominal GDP of the whole economy and $\xi^{\mathrm{SB}}_t \sim U\left(0, \xi^{\mathrm{SB}}_+\right)$ is a random shock.

Here, ξ^{SB}_+ is kept small (at 1%), such that social spending does not react too strongly to business cycle fluctuations, and debts are brought back to target over a long period of time such that the government does not have a strong pro-cyclical effect on macroeconomic outcomes. In this version of the model the government is kept 'small' as to fully illustrate the shock transmission through the various markets, sectors and regions (see Section 4 for further discussion and suggestions for future work). Because of this, the government also does not provide emergency aid or disaster loans to firms or households during the shock aftermath. Our sensitivity analysis in the supplementary material show that the parameters used for governmental spending do not change our result qualitatively, nor have a large quantitative impact.

Lastly, the unemployment benefits y^{UB} are held constant throughout the simulation. These also set the effective minimum wage $w^{\min}$, as firms always set a minimum offered wage of $w^{\min} = y^{\mathrm{UB}}/0.7$, such that the unemployment benefits are always at most 70% of the lowest possible wage.

A.2.2. Mutual fund

Each month, the mutual fund receives dividends R_t^{Div} from firms and pays out venture capital C_t^{VC} to new firms and capital income C_t^{CI} to households. The total amount of venture capital depends on the number of newly introduced firms, and how large the production targets of these firms are when they enter (see Section 2.2.1).

The mutual fund cash balance C_t^{CF} then evolves as $C_t^{\mathrm{MF}} = C_{t-1}^{\mathrm{MF}} + R_t^{\mathrm{Div}} - C_t^{\mathrm{VC}} - C_t^{\mathrm{CI}}$. In order to ensure stable venture capital and capital income payments, the mutual fund sets a cash balance target $\widetilde{C}_t^{\mathrm{MF}} = \phi^{\mathrm{MF}} R_{t-1}^{\mathrm{Div}}$, $\phi^{\mathrm{MF}} \geq 0$. We assume the mutual fund prioritizes venture capital investments, and therefore adjusts its payout of capital income in order to let the cash balance C_t^{MF} be equal to the target $\widetilde{C}_t^{\mathrm{MF}}$. It does so using a similar rule as the government:

$$C_t^{\mathrm{CI}} = \begin{cases} C_{t-1}^{\mathrm{CI}}(1+\xi_t^{\mathrm{CI}}) & \text{if } C_{t-1}^{\mathrm{MF}} > \widetilde{C}_{t-1}^{\mathrm{MF}} \text{ and } R_t^{\mathrm{Div}} > C_t^{\mathrm{VC}} + C_t^{\mathrm{CI}}, \\ C_{t-1}^{\mathrm{CI}}(1-\xi_t^{\mathrm{CI}}) & \text{if } C_{t-1}^{\mathrm{MF}} < \widetilde{C}_{t-1}^{\mathrm{MF}} \text{ and } R_t^{\mathrm{Div}} < C_t^{\mathrm{VC}} + C_t^{\mathrm{CI}}, \\ C_{t-1}^{\mathrm{CI}} & \text{else,} \end{cases} \tag{A.2}$$

where $\xi_t^{\mathrm{CI}} \sim U\left(0, \xi_+^{\mathrm{CI}}\right)$ is a stochastic shock. Once the total spending on capital income is determined, the capital income paid to household j is proportional to its current stock of liquid wealth:

$$y_{j,t}^{\mathrm{CI}} = C_t^{\mathrm{CI}} \frac{W_{j,t}}{\sum_{k\in\mathcal{H}} W_{k,t}}. \tag{A.3}$$

A.3. Market interactions

A.3.1. Inter-regional trade

Inter-regional trade is costly. Here, we make use of 'iceberg' trade costs (as is common in models on trade and regional economics (Fujita et al., 1999)). Trade costs are modeled using a trade markup $\vartheta \geq 1$, where trade *within* a region is not costly ($\vartheta_{r,r} = 1$) and trade *between* regions is costly ($\vartheta_{r',r} > 1$, $r' \neq r$). This is symmetric between regions (i.e. $\vartheta_{r',r} = \vartheta_{r,r'}$). Then, if a buyer in region r wants G units of good from a seller in region r', it has to buy $G\vartheta_{r',r}$ units, to only receive G units, which therefore increases the *effective* unit price by a factor $\vartheta_{r',r}$. We provide some further discussion on the use of iceberg trading cost in the supplementary material.

A.3.2. Consumer goods and services markets

Demand of households for CG and CS is based on the price asked by the firm (incorporating the trade cost) and the desire for product 'variety'. Each firm computes its market share in region r as follows:

$$m_{i,r,t} = \frac{\left(p_{i,t}\vartheta_{i,r}\right)^{-\gamma^{dH}}}{\sum_{k\in\mathcal{F}_s}\left(p_{k,t}\vartheta_{k,r}\right)^{-\gamma^{dH}}}, \tag{A.4}$$

where $\mathcal{F}^s$ are all firms in the same sector as i, and γ^{dH} represents the 'preference for variety', as in the seminal model by Dixit and Stiglitz (1977) of monopolistic competition. A higher value of γ^{dH} means households select more on price, resulting in a higher degree of market concentration. As discussed in Section 2.2.1, firms with higher A_i are able to ask a lower unit price, which means a higher value of γ^{dH} leads to a higher market concentration with more productive firms. In our calibration, this market matching setup allows for firms of different productivity levels to co-exist, as lower productive firms with higher prices still receive some demand, giving rise to the stable productivity-to-sales shown in Appendix B. This means shocks to firms to different productivity levels capture the impact of shocks to differently sized firms.

The real demand for firm i's output is then given as:

$$d_{i,t} = \sum_{r\in\mathcal{R}}\left[m_{i,r,t}\sum_{j\in\mathcal{H}_r} d_{j,s,t}\vartheta_{i,r}\right], \tag{A.5}$$

with $\mathcal{R}$ being the set of regions (i.e. exposed and safe). Note that this simplifies for CS-firms, as their output is not tradable and the market share is only computed within their own home region. After receiving demand $d_{i,t}$, firms determine how much demand could not be met (as described in Section 2.2.1).

A.3.3. Capital goods market

The capital goods market is modeled as a dynamically evolving network of suppliers and buyers. Each firm has a set of KG-suppliers $\mathcal{F}_{i,t}^K$ of fixed size $N_{\mathcal{F}^K}$, where a KG-firm cannot buy its own capital goods. When the firm desires additional capital ($K_{i,t}^d > 0$), it will place offers among the firms in $\mathcal{F}_{i,t}^K$. Here, we use a similar approach as Eq. (A.4), where firm i's order of capital goods to KG-firm l is:

$$d_{i,l,t}^K = K_{i,t}^d \frac{\left(p_{l,t}^K\vartheta_{i,l}\right)^{-\gamma^{dF}}}{\sum_{k\in\mathcal{F}_{i,t}^K}\left(p_{l,t}^K\vartheta_{i,k}\right)^{-\gamma^{dF}}} \tag{A.6}$$

Note that capital comes in discrete 'machine' units, each with $K^{\mathcal{M}}$ capital units. The ordered amount is rounded to the nearest possible number of machine units.

The supplier network evolves as firms update $\mathcal{F}_{i,t}^K$ for two reasons: price competition and unmet demand. Firstly, every period the firm decides for every $l \in \mathcal{F}_{i,t}^K$ whether to switch to an alternative supplier l', which is sampled from the pool of non-connected KG-firms. This is done with probability:

$$\mathbb{P}(\text{switch on price})_{i,l,l',t} = 1 - \exp\left(-\gamma^{\mathrm{SwP}}\frac{p_{l,t}\vartheta_{i,l} - p_{l',t}\vartheta_{i,l'}}{p_{l',t}\vartheta_{i,l'}}\right). \tag{A.7}$$

So a larger difference in effective unit price leads to a larger probability of switching. Secondly, the firm may switch from l to a randomly selected l' if its demand for capital goods is not met. The probability of switching is based on the ratio of unmet demand $d_{i,l,t}^u$ to total demand:

$$\mathbb{P}(\text{switch on unmet demand})_{i,l,l',t} = 1 - \exp\left(-\gamma^{\mathrm{SwU}}\frac{d_{i,l,t}^u}{d_{i,l,t}}\right). \tag{A.8}$$

Through these switching rules, the network of KG-suppliers dynamically evolves to favor more competitive firms that are able to meet demand.

A.3.4. Labor market

Labor market matching is modeled as 'competitive search', where firms publicly post wages, and job-seeking households are more inclined to apply to positions that offer a higher wage (Rogerson et al., 2005). The wage setting and determining of labor demand $L_{i,t}^d$ was described in Section 2.2.1. Based on the labor demand, the firm sets out a number of vacancies $L_{i,t}^V = L_{i,t}^d - L_{i,t}$, where they enter the labor market if $L_{i,t}^V > 0$. Firms with $L_{i,t}^V < 0$ will fire workers, where they fire in order of the highest to lowest wage.

The total number of applicants in the region $L_{r,t}^A$ – consisting of all unemployed households and all households deciding to switch employment – is then divided to give each hiring firm $L_{i,t}^A$ applicants in the following way:

$$L_{i,t}^A = L_{r,t}^A \frac{L_{i,t}^V\left(w_{i,t}^o\right)^{\gamma^w}}{\sum_{k\in\mathcal{F}_r} L_{k,t}^V\left(w_{k,t}^o\right)^{\gamma^w}}. \tag{A.9}$$

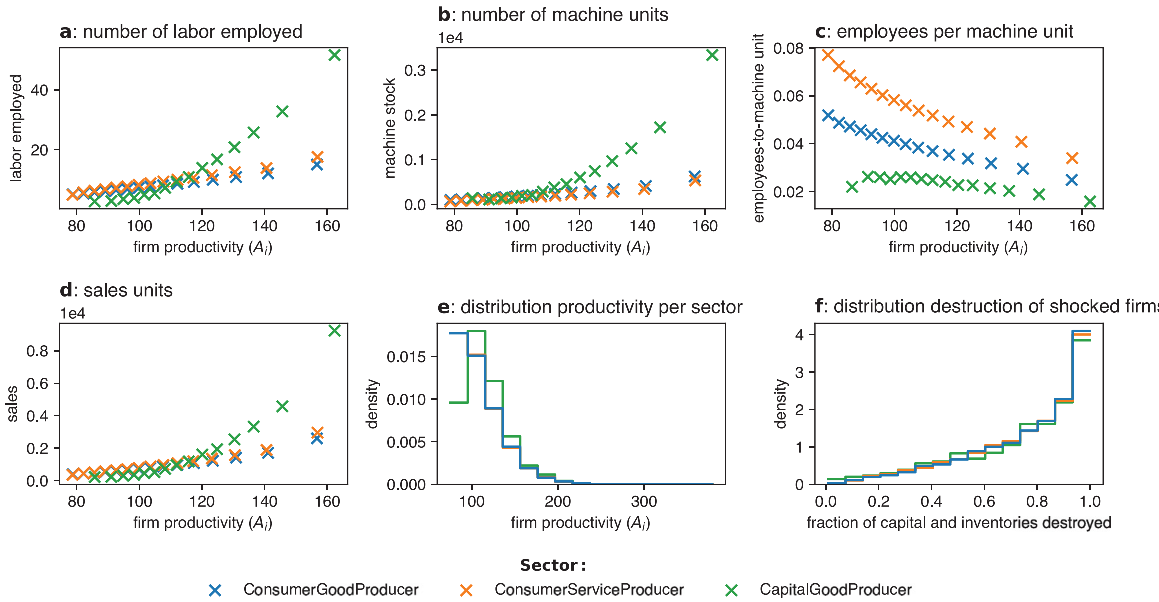

Fig. B.8. Firm-level data for the 100 different seeds at the time step before the flood shock. For **a-d**, the values shown are the average within 20 bins of values of A_i, where each bin contains the same number of firms. For **e** the distribution of A_i, one step before the shock, per sector is shown for all 100 simulations, combined. For **f** the density of the fraction of destroyed capital and inventories (ξ_i^{ND}) is shown (only for affected firms) for Setup III (*heterogeneous & concentrated*) for all 100 simulations.

Here γ^w is the elasticity of labor supply to the offered wage. Given $L_{i,t}^V$ and $L_{i,t}^A$ the firm then updates its offered wages according to Eq. (6).

Appendix B. Additional results

B.1. Firm-level results

Fig. B.8 shows how the number of employees, the labor-to-machine ratio and the sales in units relate to the productivity level of the firm. Here, it can clearly be seen that more productive firms hire more employees, sell products, and are more capital intensive (i.e. less labor employed per machine) than their less productive counterparts. We can also see that the capital good sector is more concentrated than the other two sectors. This is because the firms more strongly select a supplier for price, and firm-to-firm trade relations are more strongly penalized for unmet demand, which is more likely for smaller firms with a lower productive capacity.

B.2. When does heterogeneity matter?

Fig. B.9 compares how selecting for productivity (Fig. B.9.a), capital intensity (Fig. B.9.b) and financial fragility (Fig. B.9.c) affect outcomes in the short run (after 1 year) and long run (after 10 years). Here, financial fragility is defined as the ratio of the firm's cash buffers to its outgoing expenses, and capital intensity as the κ-parameter. A detailed discussion of the experimental setup and results is provided in the supplementary material.

Appendix C. Related models and extensions

The EMERGO model drawns upon a range of models from the macroeconomic agent-based modeling tradition. These computational models explicitly represent individual agents (typically households and firms) as software objects. These agents employ some form of behavioral heuristics (Simon, 1955) and act and interact with other agents bases on limited information. These models cannot be solved analytically, but are solved "from the bottom up" through simulation. This means there are no explicit equations for aggregate variables such as GDP or inflation, but these are computed by aggregating over the micro-states of the individual agents (Dawid and Delli Gatti, 2018) — much like how these aggregate variables would be computed in reality. This flexibility at the agent-level enables a large degree of heterogeneity in agent characteristics and behaviors. Furthermore, no strict conditions are imposed on market clearing, which means markets and economies can operate 'out-of-equilibrium' for an extended period (Arthur, 2006).

Within this literature, the EMERGO model incorporates multiple elements of the 'adjustment heuristics' approach (Fagiolo et al., 2019). Here, agent behave in accordance with basic economic principles, but do so based on simple behavioral rules and local information, as they only have limited computational capacities. These elements can be seen, for instance, in how firms set investment growth (Eq. (3)) or the price setting (Eq. (5)). This approach ensures that the emergent macro-dynamics result from logical micro-foundations.

The EMERGO model is further extended to accommodate the regional economic transmission of natural disaster shocks. Here, the model is most closely related to the Climate-economy Regional Agent-Based (CRAB) model (Taberna et al., 2022, 2023a), both in terms of regional and sectoral structure, as well as how agents are shocked. The focus of EMERGO is more on how the decentralized market processes affect individual firms (through the adjustment heuristics described above), and how these may lead to post-shock out-of-equilibrium dynamics, as well as steady state aggregate dynamics (which is further described in the supplementary material).

Lastly, the EMERGO model incorporates ideas on agent-based stock-flow consistency (Caiani et al., 2016). In particular, the consistent accounting of cash holdings and inventories allows to study how buffers at the micro-level can impact macro-outcomes. This allows modeling agent-level stock constraints to recovery, such as financial constraints (Basker and Miranda, 2018) and inventories (Hallegatte, 2014).

Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ecolecon.2026.109037.

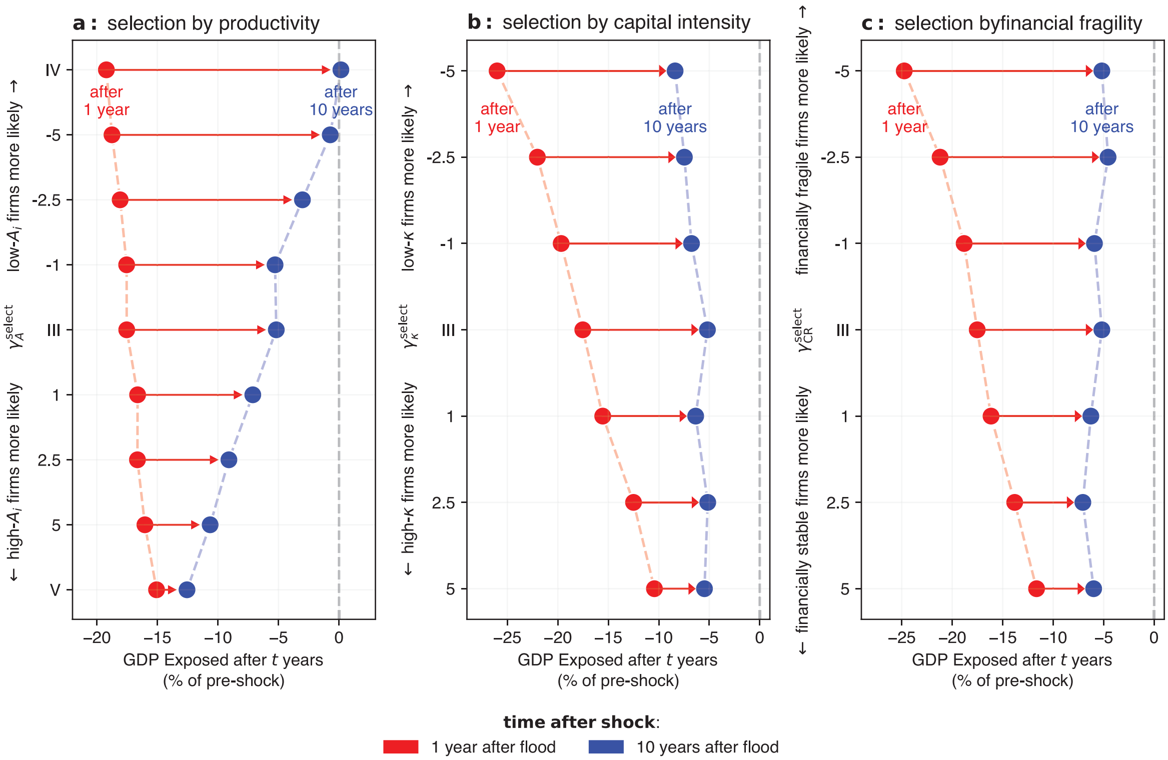

Fig. B.9. Mean change in GDP of the exposed region relative to the pre-shock level 1 year after the flood event and 10 years after the flood event. For a-c, firms are selected to be shocked based on a given characteristic (A_i, κ or financial fragility). The y-axis either shows the scenario (III, IV or V), or the elasticity of choice by the characteristic. Furthermore, Setup III is taken as the middle value, as here firms are not selectively shocked based on any characteristic. For (a) the results for Setup IV and V are taken as the extremes of selection by productivity. Each configuration of selection intensity was sampled 30 times.

Data availability

The code used to produce the results will be made available publicly at the time of publication.

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