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ORIGINAL ARTICLE

Revealing indirect risks in complex socioeconomic systems: A highly detailed multi-model analysis of flood events in Austria

Gabriel Bachner[1] | Nina Knittel[1] | Sebastian Poledna[2] | Stefan Hochrainer-Stigler[2] | Karina Reiter[2]

[1]Wegener Center for Climate and Global Change, University of Graz, Graz, Styria, Austria

[2]Advancing Systems Analysis Program, Systemic Risk and Resilience Research Group, International Institute for Applied Systems Analysis, Laxenburg, Lower Austria, Austria

Correspondence
Gabriel Bachner, Wegener Center for Climate and Global Change, University of Graz, Brandhofgasse 5, 8010 Graz, Austria.
Email: gabriel.bachner@uni-graz.at

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Abstract
Cascading risks that can spread through complex systems have recently gained attention. As it is crucial for decision-makers to put figures on such risks and their interactions, models that explicitly capture such interactions in a realistic manner are needed. Climate related hazards often cascade through different systems, from physical to economic and social systems, causing direct but also indirect risks and losses. Despite their growing importance in the light of ongoing climate change and increasing global connections, such indirect risks are not well understood. Applying two fundamentally different economic models—a computable general equilibrium model and an agent-based model—we reveal indirect risks of flood events. The models are fed with sector-specific capital stock damages, which constitutes a major methodological improvement. We apply these models for Austria, a highly flood exposed country with strong economic linkages. A key finding is that flood damages pose very different indirect risks to different sectors and household groups (distributional effects) in the short and long-term. Our results imply that risk management should focus on specific societal subgroups and sectors. We provide a simple metric for indirect risk, showing how direct and indirect losses are related. This can provide new ways forward in risk management, for example, focusing on interconnectedness of sectors and agents within different risk-layers of indirect risk. Although we offer highly relevant leverage points for indirect risk management in Austria, the methodology of analyzing indirect risks can be transferred to other regions.

KEYWORDS
agent-based modeling, Austria, computable general equilibrium, flood risk, indirect risk, macroeconomic modeling

1 | INTRODUCTION

Natural disasters can propagate across different systems (e.g., physical, social, or economic) causing not only direct losses, that is, caused by the event itself, but also indirect effects, that is, effects which do not occur through the event itself but subsequently via connections between system elements. Indirect risks due to natural disasters are a growing concern for many risk bearers around the world, including the private sector as well as governments, and even more so in the light of ongoing climate change which is expected to increase frequency and intensity of extreme events (IPCC, 2021). In that context in the past few years "complex cascades" (Reichstein et al., 2021) received particular attention, including the impact of compound events (i.e., the combination of processes, (Zscheischler et al., 2020)), for example in regards to critical infrastructure (Wells et al., 2022), natural hazards (Cegan et al., 2022), or financial risks (Hochrainer-Stigler, 2021).

As a case in point, in socioeconomic complex systems indirect risk often materializes via transport disruptions or business interruptions (Hochrainer-Stigler et al., 2018; Kurth et al., 2020). For instance, the 2011 Tohoku earthquake and tsunami that followed, disrupted the production of critical components that lead to significant production losses worldwide (WEF, 2012). Indirect risk is thus indeed significant and can strongly amplify direct risks (Bachner et al., 2022; Hallegatte et al., 2007; Mandel et al., 2021). This is particularly the case for industrialized countries, as they are characterized by a high degree of specialization and strong inter-sectoral dependencies and feedbacks. Moreover, risk is also propagating via trade across country borders (Bednar-Friedl et al., 2022; Carter et al., 2021), adding to the complexity (Centeno et al., 2015).

The concept of "resilience" proved to be useful to respond to the complex nature of the problem. It describes a system's "ability to cope with shocks and to keep functioning in much the same kind of way" (Walker, 2020, p. 1). The resilience perspective can help in analyzing and structuring the management of indirect risk. Hynes et al. (2022) categorized resilience into "resilience by intervention" and "resilience by design." The former describes the reactive dimension of risk management, which is currently at focus in economic recovery policies (most often in the form of government relief programs). This approach, however, often leads to unexpected knock-on effects, and might reach its (budgetary and political) limits when costs of intervention are rising. Contrary, "resilience by design," describes the proactive dimension, with the aim to restructure economic systems such that they can absorb shocks in a self-organized way without losing its functioning (Rözer et al., 2022). This reduces the need for policy interventions and costs in the long-term. Examples of the application of the concept of resilience are Kurth et al. (2020), who demonstrate how the lack of resilience of transport network translates into economy-wide losses, Salem et al. (2020), who develop a probabilistic resilience quantification framework for infrastructure management or De Bruijn (2004), who develops indicators for the resilience of flood risk management.

Although one can acknowledge that large uncertainties and ambiguities arise if risk propagation in complex systems and their dynamics are studied (Renn et al., 2022), and therefore usually a mixture of different strategies (e.g., based on frequentist approaches, precautionary principles, or discursive strategies (see for example Renn et al., 2011) may seem as most appropriate, the need for quantitative assessment of such indirect risk is emphasized lately, especially for climate related hazards (Reichstein et al., 2021). Hence, to support policymakers and investors in their risk management strategies, quantitative models that explicitly capture the interactions of direct and indirect risks are crucial. Having such models at hand is a prerequisite to answer the questions of (i) how indirect risks emerge, (ii) how strong indirect risks are for different actors and ultimately, and (iii) how indirect risks can be decreased.

In this article, we respond to this need by developing and using two highly detailed modeling approaches: A high resolution computable general equilibrium (CGE) model and a macroeconomic agent-based model (ABM), both being fed with different flood scenarios from a probabilistic catastrophe simulation model, further called "damage scenario generator." We calibrate and apply these models for the case of flood risk in Austria, a highly developed country with a strongly interconnected economy. Austria is facing high risks from riverine floods, as visible in recent events, and consequently also high indirect risks. In addition, the Austrian National Climate Change Adaptation Strategy recommends risk-based approaches in many cases (BMNT, 2017a, 2017b). Besides Austria being exposed to flooding, spatially explicit economic data are available, which allows us to relate them to hazards and therefore to calibrate and use the economic models on a very high sectoral resolution. To the authors' best knowledge, this has not yet been done.

State-of-the-art methods for economy-wide analysis of disasters are input output (IO) modeling (see e.g., Hallegatte, 2008) as well as CGE modeling (Tirasirichai & Enke, 2007; Xie et al., 2018), both being able to capture indirect effects in terms of interlinkages across producers and consumers. Although IO modeling is seen useful for very short-term analysis due to the assumed rigidity of production functions, CGE models are more flexibility in terms of economic dynamics, responses, and feedbacks of economic agents. Yet, due to data limitations CGE modeling studies so far have implemented economic damages from disasters in a rather coarse way, that is, by reducing the generic economy-wide capital stock of the economy (see e.g., Gertz et al., 2019). This is problematic, though, as it implies that it is capital-intensive sectors that are affected in the first place, even though their assets might not be exposed to hazards at all (Bachner, 2017).

In this article, we overcome this problem by using a spatially explicit approach for damage calculations, combined with a detailed firm-level dataset, which are fed into a highly resolved CGE model. In addition, we apply a relatively new method, that is, a complex ABM at the individual (firm) level that allows for system emergence. ABMs are increasingly used in the context of flood risk, however, at rather small scales such as communities (see e.g., Tonn et al., 2020; Tonn & Guikema, 2018). The here presented ABM is calibrated to a whole country, which is a major methodological step forward. This multi model assessment allows us to identify model uncertainty as well as model features that drive differences in model outcomes. Complementary to the individual models' results we thus synthesize and discuss strengths and weaknesses of each approach as well as the resulting uncertainties.

Our article is organized as follows. Section 2 starts with a description of the damage scenario generator (DSG) as well as the CGE model and the ABM. Section 3 presents results and important findings for each model. After that, Section 4 provides a discussion of results and uncertainties and gives conclusions.

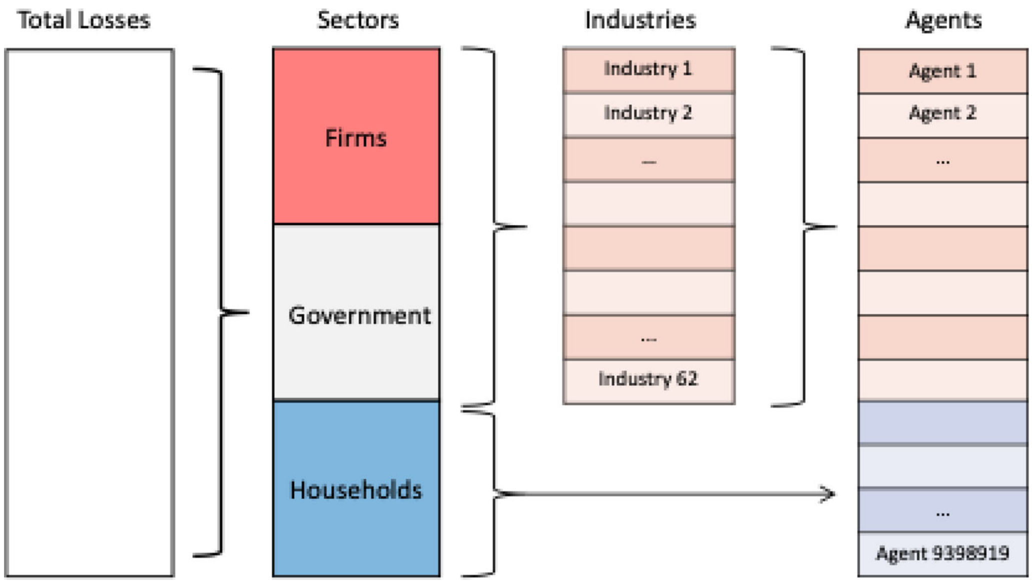

FIGURE 1 Distribution of total losses to institutional sectors, industry sectors, and individual agents.

2 | METHODOLOGY

2.1 | Damage scenario generator

2.1.1 | Estimation of agent-specific losses

We feed the two macroeconomic models, with the results of a DSG. Flood damage estimation is usually done via so-called catastrophe modeling approaches (Grossi & Kunreuther, 2005; Hand, 2011) where losses are a function of natural hazard, exposure, and vulnerability. We refer to Botzen et al. (2019) for a review and to Ward et al. (2013) for an application of a flood damage model at the global scale. Similarly, our DSG combines hazard, exposure, and vulnerability dimensions to constitute flood damages for a range of occurrence probabilities. Flood hazard information is based on LISFLOOD (a hydrological flood model) and corresponding local losses are taken from Jongman et al. (2014). These losses are upscaled to the country level using a copula-approach to avoid underestimation of risk (Timonina et al., 2015, Schinko et al., 2016). Total country level losses are finally related to sectors, industries, and agents for different events (Figure 1). More than 125,000 spatially explicit different real-world firms, their allocation to economic sectors and respective flood hazard zones are combined to estimate potential losses. As an outcome the DSG provides agent-specific losses and corresponding event probabilities for different extreme flood events (see Supplement 1 for details).

2.1.2 | Scenarios

We differentiate between two types of scenarios: a baseline and an impact scenario. The baseline depicts the evolution of Austria's economy without any flood events, whereas in the impact scenario, in addition, flood damages hit the economy in the first time-step of analysis. By comparing the impact scenario to the baseline, we isolate the effects of flood damages to the economy in the period of the disaster and beyond.

Table 1 shows the selected scenarios, including two extreme ("Armageddon") scenarios. The scenarios are selected according to risk-layers (Mechler et al., 2014) which distinguish frequent, less frequent, and very rare events according to their occurrence probabilities. The Armageddon scenarios were selected based on stakeholder interactions (Reiter et al., 2022) and previous studies (Poledna et al., 2018). Note, that the Armageddon scenarios are illustrative and highly unlikely, serving to show possible nonlinear economic effects under severe stress.

2.2 | Computable general equilibrium model

2.2.1 | General description

CGE models are based on IO tables and divide the economy into several economic production (or industry) sectors as well as final demand agents. Due to the underlying IO structure, CGE models explicitly capture connections across all sectors and agents via demand and supply dependencies, measured in monetary flows. CGE models are thus able to explore how a localized "shock" ripples through the economic system, leading to indirect effects, for instance from damages to the capital stock due to a weather-related shock.

The main idea behind CGE models is, that market forces lead the economy toward a situation in which all markets are simultaneously in equilibrium (where supply equals demand) or put differently, a flow equilibrium of monetary streams. Such a "general equilibrium" describes an economic state of optimality, which implies that production capacities are fully/optimally utilized and thus scarce. The economy is thus

TABLE 1 Scenario overview

Scenario	Percent of capital stock destroyed[a]	Damage in million €/characterization
20-year event		932
100-year event		7748
1000-year event		17,349
Armageddon scenario I	3%[b]	1000-year event in all basins simultaneously
Armageddon scenario II	5%	Selected scenario for interest by stakeholders and literature

[a]For the 20, 100, and 1000-year event: depending on the underlying database and model.
[b]Approximately.

supply-side constrained and there is neither excess-supply nor excess-demand of goods, services, and production factors (typically capital and labor).

A key feature of CGE models is that they allow for endogenous changes in relative prices and—based on that—for substitution processes within production and consumption according to elasticities of substitution. Specifically, sectors and final demand agents are assumed to minimize production costs and maximize utility, respectively, using constant elasticity of substitution production/utility functions calibrated to observed behavioral parameters. These endogenous adjustment processes of prices and quantities are nonlinear and set CGE models apart from rather rigid conventional IO models.

Assuming that the economy is initially in a state of equilibrium, one can disturb it by an exogenous shock, thereby triggering the described adjustments processes. Ultimately this process leads to a new equilibrium, but at different prices and quantities than initially. By comparing the new equilibrium to the old one, one can isolate the effects of the exogenous shock, for example, by how much prices, sectoral outputs, value added, or GDP have changed.

In this analysis, we use and build upon the model of Mayer et al. (2021). It is a recursive-dynamic, multi-sector, and small-open-economy model of Austria, which comprises 74 economic production sectors, 12 private demand agents (representative households, differentiated by income and location of residence), and 1 public agent (household). The original model has been refined in two ways. First, capital is sector-specific (immobile), which comes closer to a short-run representation. Second, sectoral investment is modeled endogenously, based on capital rents.

There are two production factors, which limit the economy-wide production capacity: capital and labor. Capital accumulates sector-wise over time and capital rents are flexible (change according to demand). Labor is generic (perfectly mobile) and its supply grows exogenously with working-age population. We assume full employment, that is, labor is scarce and wage rates flexible (see Supplement 2 for details).

2.2.2 | Implementation of flood damages

In general, capital accumulates over time as follows: The capital stock (KS) of sector i in the next year period ($t + 1$) is determined by the sector's current year (t) capital stock, minus deprecation (according to the depreciation rate δ), and plus current period economy-wide investments (I) times an endogenous sectoral investment share (τ). Flood damages are implemented as a reduction of the sector-specific capital stock, reducing production capacities. As capital accumulates over time, a reduction of capital in one period also results in a long-term effect on the economy. Capital damaged enters the capital accumulation equation as a negative component $D_{i,t}$. This setup is formulated as

$$KS_{i,t+1} = (KS_{i,t}\ \ (1-\delta)) + (I_t\overline{\tau_i}) - D_{i,t}.$$

Reconstruction is modeled as additional forced investments. In a CGE framework with no idle production capacities this implies that other economic activity is crowded out by reconstruction. Specifically, we assume that investment and consumption are crowded out by the same percentage. Note that the additional investment (reconstruction) also builds up the capital stock; however, as it partly crowds out generic investment elsewhere, the capital stock does not reach its original level in the next period. With reconstruction, capital accumulation is formulated as

$$KS_{i,t+1} = (KS_{i,t}\ \ (1-\delta)) + (I_t\bar{\tau}_i) - D_{i,t} + R_{i,t},$$

with $R_{i,t}$ being sectoral reconstruction. We assume that the size of the total investment for reconstruction is equal to the total damage to the capital stock. Hence, $+R$ compensates for $-D$, but as investment is crowded out, I is reduced, and thus, KS in the next period is smaller than without the shock. Reconstruction covers replacement/repair of buildings, machinery, and vehicles. Additionally, we assume that labor costs for clearing up in the aftermath of the event is 10% of the capital damage.

2.3 | Agent-based model

2.3.1 | General description

Macroeconomic ABMs explain the evolution of an economy by simulating the microlevel behavior of heterogeneous individual agents to provide a macro-level picture. They, together with general equilibrium models, such as CGE or dynamic stochastic general equilibrium models, are microfounded (Haldane & Turrell, 2018). There are, however, key differences between these two types of models. General equilibrium models assume that agents optimize rationally under perfect information, in fully dynamic models even about the future, whereas ABMs assume that agents use simple heuristics for decision making, depicting bounded rationality in navigating their complex economic environment (Poledna et al., 2023).

Here, we use the ABM developed by (Poledna et al., 2023). This ABM of the small-open-economy of Austria comprises financial firms, nonfinancial firms, households, and a general government. The firm sector consists of 64 industries, interacting through an input–output network, including imports and exports, to account for the trade linkages of domestic industries with the rest of the world. Each domestic sector consists of individual agents representing the economic entities populating the Austrian economy.

To study the economic consequences of flood damages, the model is calibrated to match the state of the Austrian economy in the last quarter of 2014 using micro and macro data from national accounts, input–output tables, government statistics, census, and business demography data. Agents have separate balance sheets that depict assets, liabilities, and ownership structures. The assets of the firm and household agents include a capital stock, which can be affected by an exogenous shock representing disasters such as flood damages. The ABM simulates then the microlevel behavior of agents in response to the shock and provides outcomes for macro variables.

Two main effects drive results: The destruction of the capital stock of firm agents reduces production capacities and leads to higher investment due to the reconstruction. This reduced production capacities of firms result in lower levels of output on the macro level, whereas increased investment has the opposite effect. Thus, in the short-run, the output is reduced, and in the medium to long run, it is driven by the increased demand for capital goods (see Supplement 3 for details).

2.3.2 | Implementation of flood damages

Building on a previous study (Poledna et al., 2018), flood damages are implemented in the ABM as a reduction of the capital stock of individual household and firm agents. Figure 2 depicts the basic structure of the ABM and the integration of the DSG, and Figure 1 visualizes the distribution of flood damages to individual agents. In the case of firm agents, flood damage reduces the production capacity. Capital accumulation is formulated as

$$K_{i,t} = K_{i,t-1} - \frac{\delta_i}{\kappa_i} Y_{i,t} + I_{i,t} - D^{flood}_{i,t},$$

where $K_{i,t}$ is the capital stock of firm i, $\frac{\delta_i}{\kappa_i} Y_{i,t}$ depreciation, $I_{i,t}$ investment, and $D^{flood}_{i,t}$ the flood damage to firm i. Desired investment in the capital stock of the firm i can then be written as follows:

$$I^d_{i,t} = \max\left(\frac{\delta_i}{\kappa_i}\min\left(Q^s_{i,t}, \kappa_i K_{i,t-1}\right) + \bar{K}_i - K_{i,t-1}, 0\right),$$

where $\bar{K}_i$ is the desired capital stock and $\frac{\delta_i}{\kappa_i}\min(Q^s_{i,t}, \kappa_i K_{i,t-1})$ the replacement investment. Thus, firms adjust their investment to the expected wear and tear of capital and increase or decrease their capital stock to the desired level. Therefore, in case of flood damage firms try to increase the capital stock back to the level of $\bar{K}_i$. Due to frictions, it may be the case that firms cannot obtain the desired amount of investment goods on the capital goods market. The amount of realized investment ($I_{i,t}$), therefore, depends on the outcome of the search-and-matching process in the capital goods market.

Similar to firms, household agents also suffer flood damage to their capital stock (dwellings). The capital stock of household h is

$$K_{h,t} = K_{h,t-1} + I_{h,t} - D^{flood}_{h,t},$$

where $I_{h,t}$ is the investment in dwellings of the hth household, and $D^{flood}_{h,t}$ is the incurred flood damage. Households attempt to reconstruct their capital stock and additionally invest a fraction of their income. Desired household investment can be written as follows:

$$I^d_{h,t} = \psi^H\, Y^e_{h,t} + R_{h,t},$$

where ψ^H is the propensity to invest out of the expected disposable income $Y^e_{h,t}$ and $R_{h,t}$ is the size of investment for the reconstruction, which we assume is funded by the general government. Similar to firm agents, the amount of realized investment ($I_{h,t}$) depends on the outcome of a search-and-matching process in the capital goods market and may be lower than the desired investment. In this case, households reconstruct their capital stock over several periods.

3 | RESULTS

3.1 | Results from the computable general equilibrium model

We structure the explanation of macroeconomic effects into two channels. First, the effects that originate from damages to the sectoral capital stocks themselves and second, the effects that are triggered by reconstruction activities. The ultimate outcome is the combined effect of these two channels.

We start analyzing our results at the point of system intervention, that is, the capital market in 2015. From the damage channel, we expect capital rents to be higher than in the baseline scenario, as the "remaining" capital of a

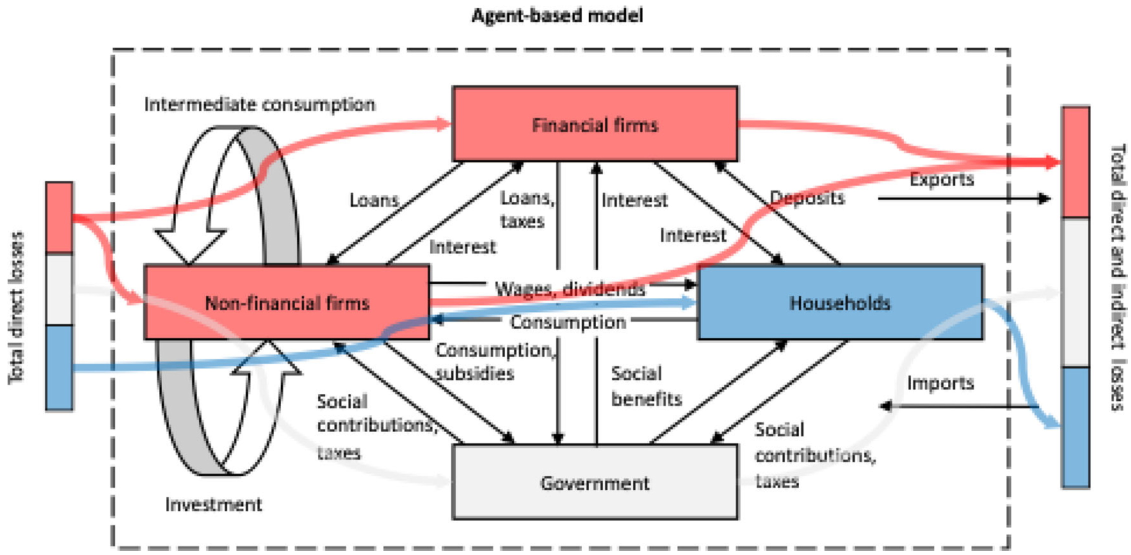

FIGURE 2 Basic structure of the agent-based model (ABM) showing the institutional sectors (households, nonfinancial and financial firms, and a general government), and their interactions. The stacked bars show an example of the distributions of direct (left) and indirect (right) total losses to the government (white), firms (red), and households (blue).

sector (the fractions that are not destroyed) is getting scarce. However, as capital is sector specific, capital rents can also decrease as a response to excess-supply pressures of capital in sectors that are not that severely affected by the flood itself, but via reduced general economic activity/demand that occurs due to reduced economy-wide income after the flood event. Additionally, we expect effects from reconstruction. Reconstruction is modeled as forced investment, which crowds out generic investment as well as consumption (see Section 2.2.2). From the reconstruction channel, we thus expect that the capital stock of those sectors that are highly demanded in reconstruction increase in their valuation and thus respective capital rents to increase. For sectors which are needed less—in particular those sectors that are providing consumption goods and services that are crowded out—capital rents are expected to decline. To summarize, the damage channel puts an upward pressure on capital rents due to scarcity, whereas the reconstruction channel works into both directions.

Figure 3 (top left) shows the change in the average capital rent. Looking at 2015, we observe that for the high impact events, average capital rents are higher than in the baseline. Only the scenarios 1/20 and 1/100 years lead to slightly lower average capital rents in the year of the flood with the positive fractions of the reconstruction channel dominating. Note, that for some sectors capital rents are also increasing in these two scenarios, though (see Supplement 4).

In the post-event years (starting with 2016), average capital rents are above baseline levels in all scenarios. This is because reconstruction investments also crowd out other generic investments, and thus, the pre-event capital stock is not established again after the reconstruction phase. Reconstruction is assumed to take place only in the year of the event; thus, what dominates in the following periods is the damage-channel, which leaves the economy with a smaller capital stock and thus higher capital rents due to scarcity. This effect is getting weaker over time since the speed of capital accumulation increases after the event due to a redistribution of income toward households with higher investment (savings) rates, and thus the capital stock grows stronger than in the baseline (see Supplement 2).[1]

We now turn to the second production factor, labor, and the associated effects on the wage rate. Again, we explain effects via the damage and the reconstruction channel. After capital destruction, labor is relatively more abundant which translates into lower wages as a response to excess-supply pressures. Hence, the damage channel puts a downward pressure on wages. The reconstruction channel affects wages via the shift from relatively labor-intensive consumption to more investment, which also leads to a downward pressure on wages.

Figure 3 (top right) shows the effects on the wage rate, relative to the baseline. Irrespective of the scenario, we observe a lower wage rate in the year of the flood event (2015), followed by a recovery. When comparing the effects between capital rents and wage rate, we observe that the labor market reacts stronger than the capital market. Note again that the reconstruction channel is only effective in the year of the flood; hence, as from 2016 onward the effect of lower wages is driven by the relative scarcity effect of capital. As the capital scarcity effect weakens over time, so does the effect on the wage rate. Interestingly, around 2020 wages start to be above baseline levels. This can be explained by two effects. First, the capital scarcity effect is weakening over time, making labor more productive again. Second, due to capital scarcity and higher capital rents, there is a redistribution of income to

[1] Note that despite the flood event leads to lower income also for higher income households, the higher savings rate of high-income households leads to stronger economy-wide capital accumulation.

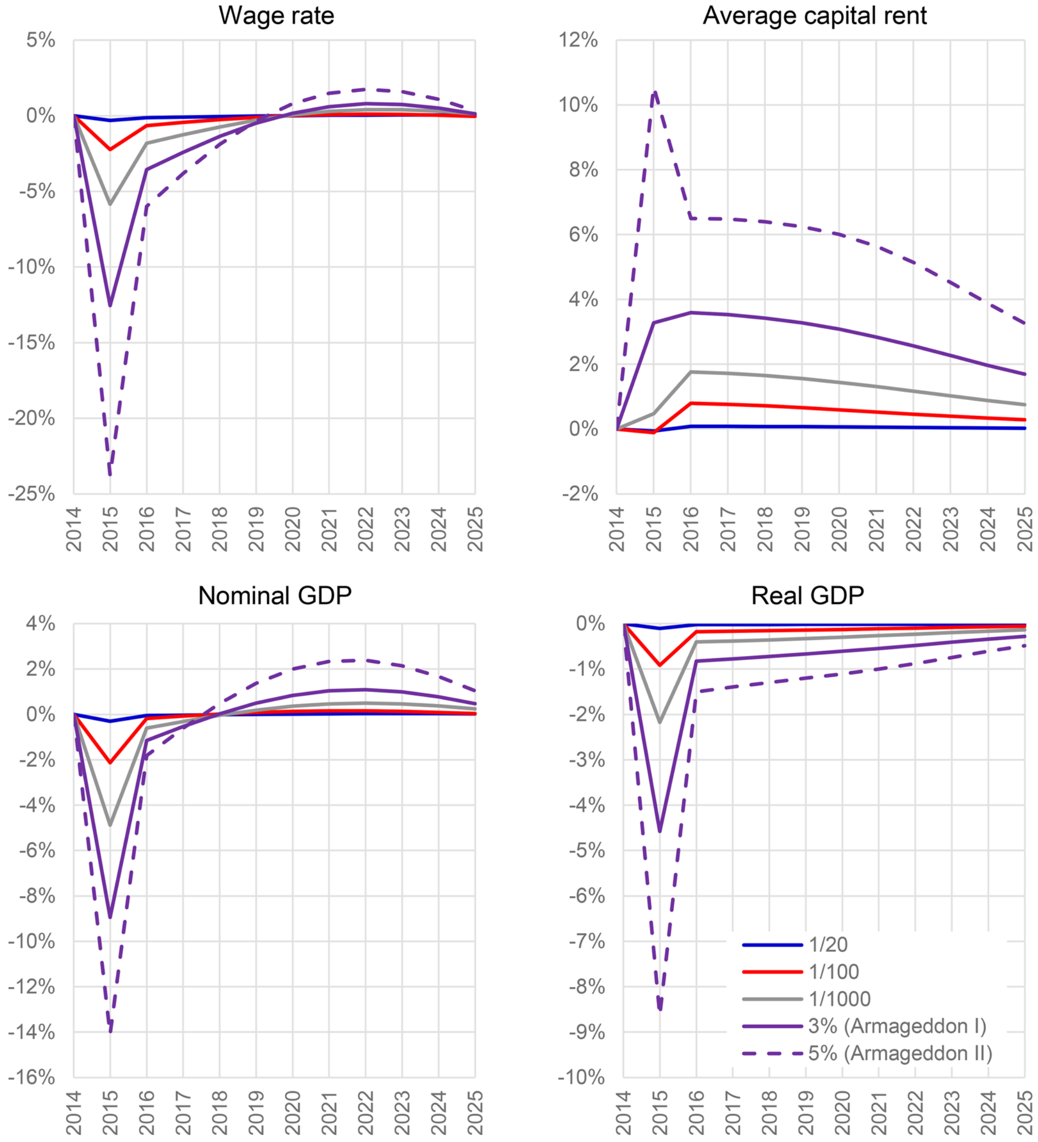

FIGURE 3 Effects on wage rates, average capital rents (weighted average over all sector-specific capital rents), nominal GDP (including relative price effects), and real GDP (at constant prices). The panels show the effects as changes relative to the baseline scenario in which no disaster happens.

higher income households (who own more of the capital stock than low-income households). As higher income households have higher expenditure shares for labor-intensive consumption than low-income households, demand for labor increases and so does the wage rate.

We now investigate economy-wide effects, by analyzing the effects on GDP (Figure 3, bottom). From the discussion on capital rents and wages, we already know how the two major income components of the economy react, which is mirrored also in nominal GDP. In fact, the effects closely follow the effect on the wage rate, as labor income is by far the largest source of income in the economy and wages react much stronger than capital rents. Figure 3 (bottom right) gives also changes in real GDP (at constant prices). Compared to nominal GDP the positive effects from higher wage rates disappear and are below the baseline throughout the whole time horizon.

We now take a closer look at distributional effects. We measure welfare effects in terms of changes in consumption possibilities after prices and incomes have changed (i.e., real consumption[2]). Figure 4 shows effects differentiated by income quartiles and location of residence illustratively for the 1/100 years scenario. In addition, we show the effect on the government's consumption, which is an indicator for public service provision, which also contributes—next to private consumption—to societal welfare. In general, welfare effects are negative, but there are strong differences across households. We see that in the year of the flood event (2015) the negative effects are strongest for high-income households (income quartile Q4) and only moderate for low-income households (Q1). This is because it is mainly higher income households who are the owners of capital and thus

[2] Hicks Ian equivalent variation

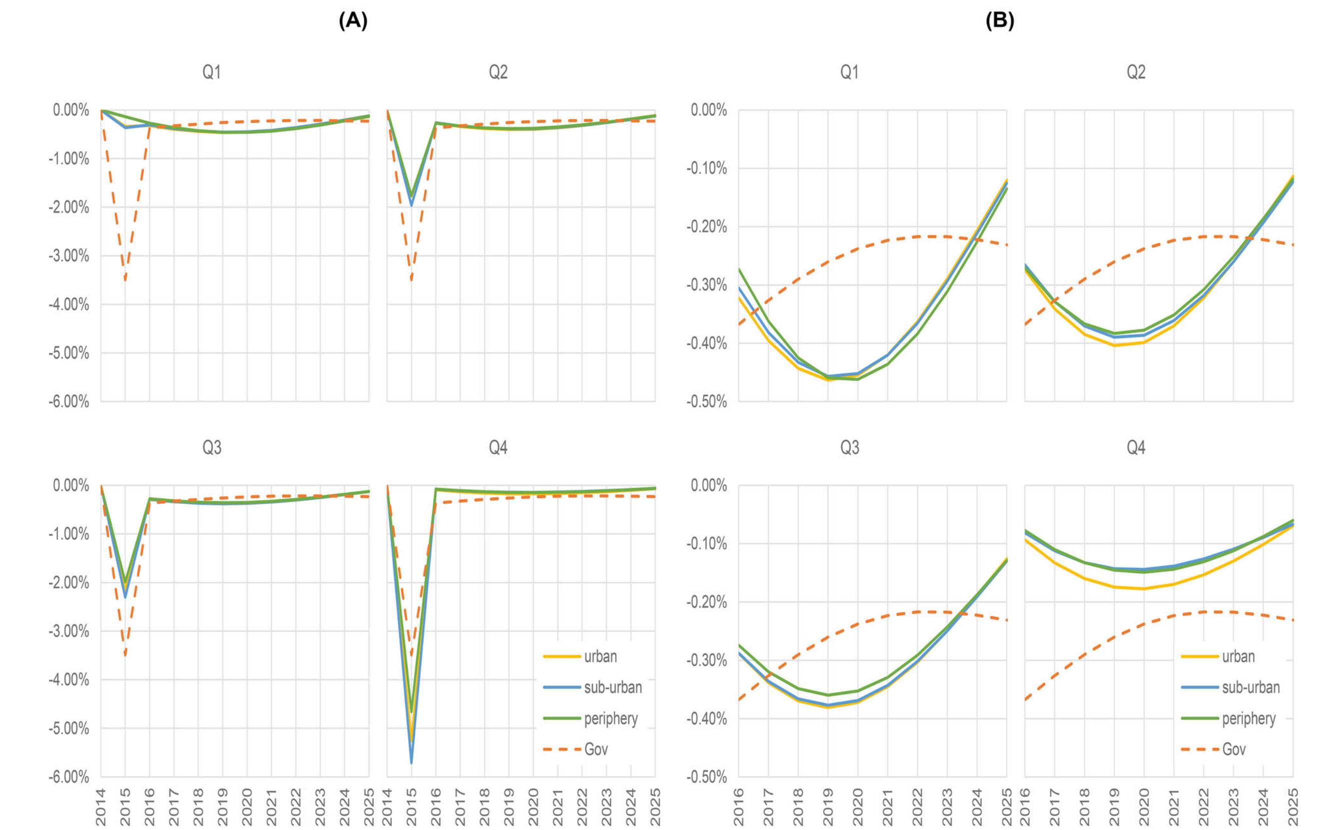

FIGURE 4 Consumption quantity effects by income quartile (Q1 = first, Q2 = second, Q3 = third, and Q4 = fourth) and location of residence (urban, suburban, and peripheral) as well as effects on quantities of public service provision (Gov) relative to baseline for scenario 1/100. Left (a): whole time horizon; right (b): only subsequent years of the flood event.

lose a higher proportion of their income due to the damages. Lower income households receive lower fractions of their income via factor provision in general (labor or capital supply), as they rely stronger on public transfers. When comparing private and public consumption, we see that all income quartiles, except for the highest one, are stronger affected by reduced public service provision than by changes in private consumption.[3]

When looking at the periods after the flood event (Figure 4, right), we see that consumption possibilities remain below the baseline level for all household types and for the government. As opposed to GDP, which also includes relative price changes as well as investment, the perspective of consumption possibilities reveals that the society as a whole suffers from a flood event even in the long-term. From this long-run welfare perspective we see that it is the low-income households that are affected strongest and that the negative effects are getting less severe with rising income. The reasons for that are twofold: First, the expenditure structure varies across income quartiles. Lower income households have higher expenditure shares for capital-intensive goods and services (such as housing), whereas higher income households have higher shares for labor-intensive consumption goods. Since capital costs (rents) increase and labor costs (wages) decrease, higher income households have a comparative advantage vis-à-vis lower income households in terms of their consumption structure. Second, also the income structure varies across household types, with higher capital income shares for high-income households and higher labor income shares for low-income households. Hence, also due to factor price changes, low-income households are worse off.

We now turn to the indirect sectoral risk. In general, sectors are not only affected by the direct damage to its capital stock (direct risk), but also via changed demand patterns. Demand for goods and services changes due to three reasons: First, there is lower economic activity due to the shock, thus lower intermediate demand. Second, there is lower income and thus lower final demand. Third, there is reconstruction, which increases demand for some activities, but also crowds out other activities.

In Supplement 4, we show sectoral output changes in 2015 with respect to the baseline for the 1/100 years scenario. Most sectors operate at a lower activity, that is, produce less, but those sectors that are highly demanded for reconstruction have a higher output (e.g., the construction sector). To get a proxy for indirect sectoral risks, we measure how much a sector loses in terms of gross value added (GVA) and relate this loss to the direct capital damage. Put differently, we mea-

[3] This is based on the assumption, that one euro of public service provision has the same welfare effect for all household types and that it perfectly substitutes for private consumption.

sure whether the direct damage to the sectoral capital stock is larger or smaller than the loss of sectoral value added after the emerging economy-wide feedback effects. We thus calculate sector i's indirect risk as $IR_i = dGVA_i/KD_i$, where $dGVA_i$ is the change in GVA of sector i, and KD_i is the capital damage to sector i's capital stock. A value of $IR > 1$ means that the lost GVA is larger than the direct capital damage ("high" indirect risk), if $IR = 1$ its losses are the same and if $0 < IR < 1$ sectoral GVA loss is smaller than the direct damage ("low" indirect risk). An $IR < 0$ means that GVA can be increased, even though there is a direct damage to the sector (benefit of flood event). Figure 5 (top) gives results for sectors with $IR > 0$, Figure 5 (bottom) gives results for sectors with $IR < 0$ (i.e., net-benefits of the damage event). We see that especially for sectors that produce goods and services for final demand, as well as goods and services of the public domain, indirect risk is very high. For some sectors, the lost GVA is even 100–1000 times higher than the direct damage, due to economy-wide feedback effects. Only about 1/3 of the sectors show a low indirect risk and those sectors which contribute to reconstruction (construction, buildings, manufacturing of cars, civil engineering, etc.) might benefit from a flood event despite being affected directly.

3.2 | Results from the agent-based model

We use the ABM to study the short to medium-term effects, that is, effects over 1–5 years, of disaster scenarios. Figure 6 depicts the indirect economic effects resulting from a 1/100 years (redline) and a 1/1000 years (black line) flood event with total direct losses (damages) amounting to about 0.7% (100-year event) and 1.57% (1000-year event) of the capital stock, respectively. The figure shows real GDP levels (upper left panel), real GDP growth (upper right panel), government debt-to-GDP ratio (lower left panel), and the unemployment rate (lower right panel) relative to the baseline scenario[4] in percentage points (pp).[5] The qualitative behavior of the 1/100 years and the 1/1000 years scenario is as follows: starting from small negative effects immediately during the first quarter after the disaster (not visible in the yearly average), effects on economic growth turn positive in the short to medium-term (2015–2016) due to reconstruction activities. Positive effects from the reconstruction are most noticeable in the first year after the flood event (2015), with an almost 2 pp GDP growth rate increase relative to the baseline scenario. Two to three years after the disaster, however, GDP growth rates return to pre-disaster values, whereas GDP remains at a higher level compared to the baseline scenario due to a multiplier accelerator mechanism (Samuelson, 1939). This qualitative behavior, that is, positive short- to medium-term and almost neutral long-term growth effects, especially of moderate flooding disasters inducing long-term positive level effects, is in-line with the literature (Cunado & Ferreira, 2014; Fomby et al., 2013; Leiter et al., 2009; Loayza et al., 2012; Raddatz, 2009).

Figure 6 further depicts the government debt-to-GDP ratio (lower left panel) and shows the dynamic of the unemployment rate (lower right panel). The change in the unemployment rate is inversely correlated to GDP growth: for the 1/100 years event and 1/1000 years event, a decline of about 2 pp 1 year after the flood consolidates in a 1 pp decrease of the unemployment rate in the medium-term in line with the effect on the GDP level. In the medium-term after the flood (2016–2019), the government debt-to-GDP ratio steadily declines to an overall decrease of more than 5 pp (1/100 years event and 1/1000 years event) due to the medium-term increases of GDP levels and the corresponding decrease of the unemployment rate.

A very extreme-disaster scenario (Armageddon 2), which corresponds to approximately 5% damage of the capital stock in Austria, is also shown in Figure 6 (purple lines). The behavior of the extreme-disaster scenario is qualitatively different from the other two scenarios: starting from negative effects immediately after the disaster, effects on economic growth turn positive in the short-term (1 year after the disaster) due to reconstruction activities, followed by a downturn in the medium-term (2017–2019). Overall, the behavior of the unemployment rate again corresponds to the changes in the level of GDP. Due to the destruction of capital stock, the output of firms is substantially reduced immediately after the disaster resulting in a reduction of GDP growth by about 2 pp and a slightly higher unemployment rate in 2015. In the short-term after the disaster, however, with substantial reconstruction activities, the output is considerably higher, culminating in a temporary economic boom with an almost 6 pp higher GDP growth rate and an about 3 pp lower unemployment rate in 2016. The economic boom is then followed by a downturn due to declining demand after the reconstruction is completed showing that an extreme disaster may induce cyclical dynamics. The behavior of the extreme-disaster scenario is also qualitatively different from the other two scenarios with respect to the debt-to-GDP ratio. Immediately after the disaster substantial decreases in government revenues from lower tax yields and higher unemployment benefits, as well as the disaster relief we assume to be provided by the government to compensate households for their losses of dwellings, lead to a more than 5 pp rise of the government debt-to-GDP ratio (see Figure 6, lower left panel). This ratio, however, declines to an overall decrease of about 2 pp in the medium-term from 2016 to 2019.

We further disaggregate effects of the extreme-disaster scenario (Armageddon 2) for industries. Figure 7 shows the effects disaggregated for 10 economic activities according to national accounting conventions. The real estate sector (sector L) as well as the sectors J, K, M, and N are substantially affected by the destruction of capital stock as sectoral output

[4] The baseline scenario describes a continuation of current trends for the Austrian economy. It serves as the benchmark against which we evaluate the indirect economic effects of the different flooding scenarios.

[5] A percentage point (pp) is the unit for the arithmetic difference of two percentages. For example, moving up from 10% to 12% is a 2 pp increase, but it is a 20% increase in what is being measured.

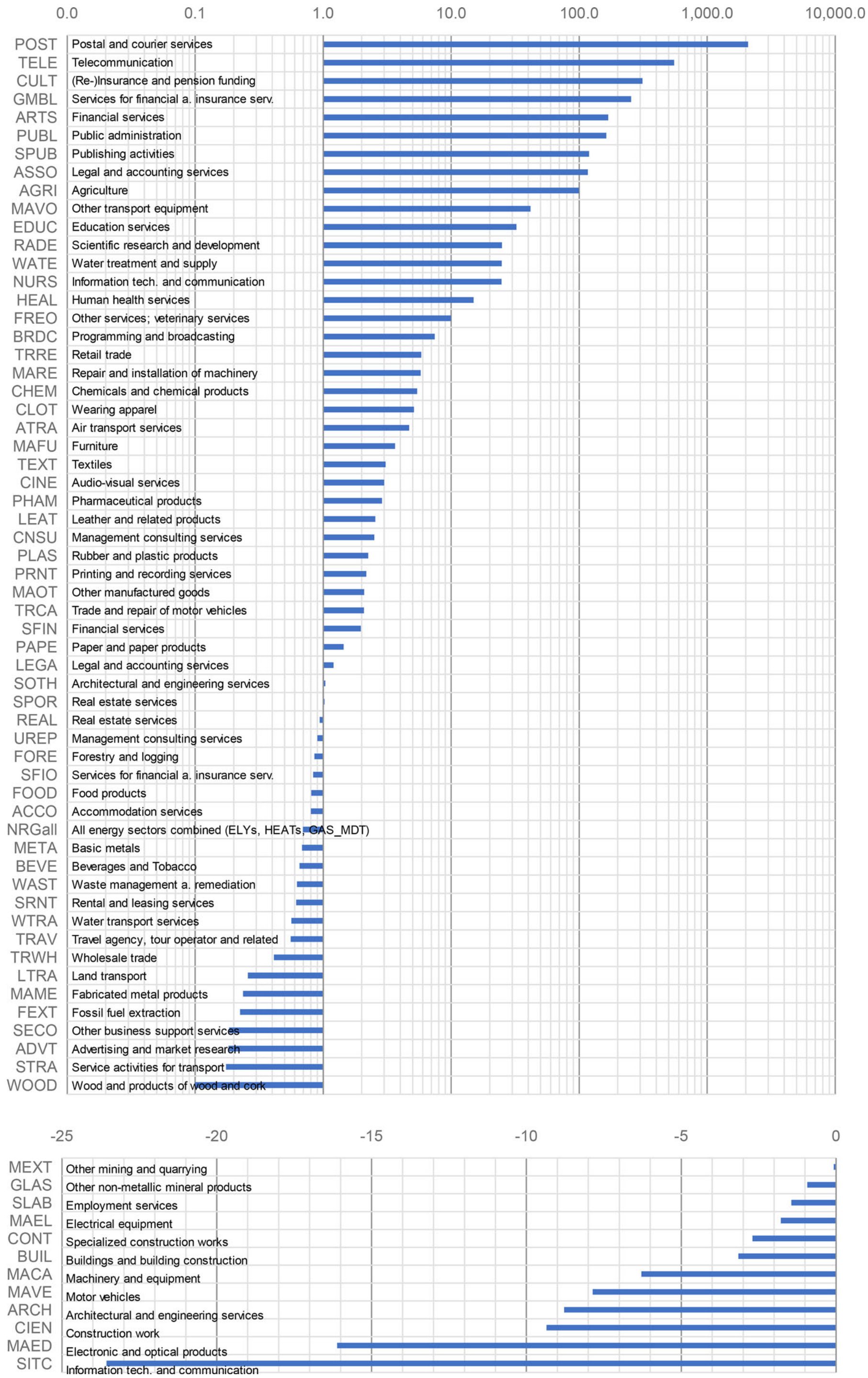

FIGURE 5 Indirect risk by sector measured as the ratio of lost gross value added (GVA) relative to direct capital stock damage in 2015 for scenario 1/100. Top: sectors with positive indirect risk (i.e., suffering losses in terms of GVA), bottom: sectors benefitting from flood events in terms of GVA, despite potential direct damages.

is reduced substantially immediately after the disaster. However, due to reconstruction activities, sectoral output soon surpasses its initial level. The construction sector (sector F) clearly benefits from the reconstruction of the capital stock in the first year after the disaster (2016). After the peak of the reconstruction, this effect gradually declines in the following years as the reconstruction of the capital stock is completed over time. The largest increase for the manufacturing industry (B–E) is also reached after 1 year of the disaster (2016) as this sector is a major supplier of the construction sector. Interestingly, even after the peak of the reconstruction in 2016, the output of the manufacturing industry remains at a higher level and only gradually returns to the level of the baseline scenario. Sectors O–Q are only slightly impacted by the dis-

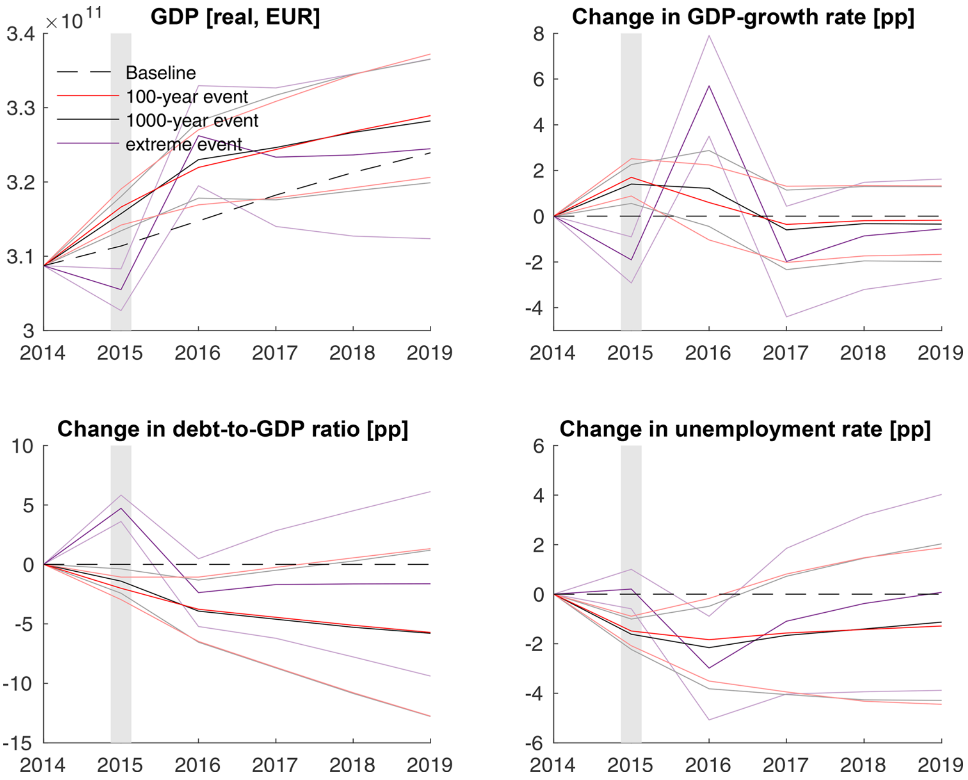

FIGURE 6 Indirect economic gains and losses of a 100-year (red), 1000-year (black), and very extreme flood event (purple = Armageddon 2). Time labels on the *x*-axis indicate the end of each year, and the grey vertical bar marks the first year after the flood. The panels show the effects as changes relative to the baseline scenario in which no disaster happens: real GDP levels (upper left panel), real GDP growth (upper right panel), government debt-to-GDP ratio (lower left panel), and the unemployment rate (lower right panel). Shaded areas cover one standard deviation above and below the mean values, as obtained from 100 independent Monte-Carlo simulations.

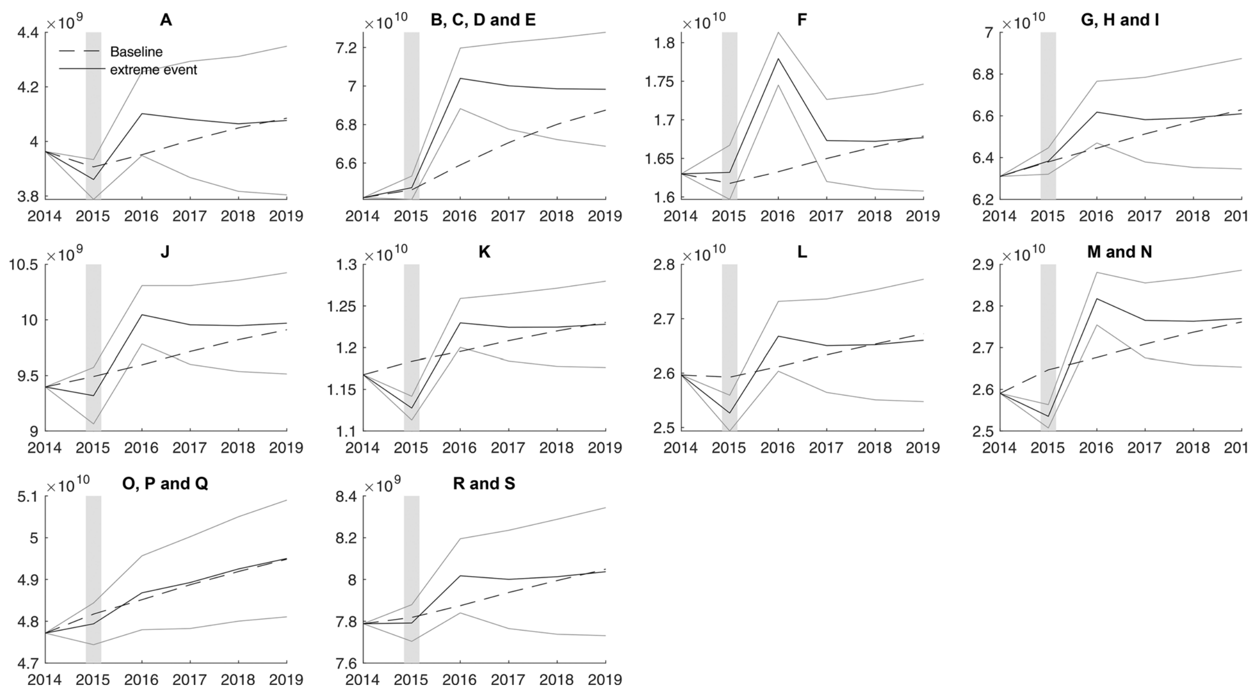

FIGURE 7 Effects of the extreme-disaster scenario (Armageddon 2) disaggregated for 10 economic activities (sectors). Sectors shown: agriculture (A), manufacturing, mining and quarrying, other industry (sectors B–E), construction (F), wholesale and retail trade, transportation and storage, accommodation and food services (G–I), information and communication (J), financial and insurance services (K), real estate activities (L), professional, scientific, technical administrative and support service activities (M and N), public administration and defence, compulsory social security, education, human health and social work activities (O–Q).

aster. The effects on all other sectors (A, G, H, I, R, and S) are somewhat less pronounced.

4 | CONCLUSIONS

4.1 | Summary

One of the key findings is distributional effects after extreme events realize. From the CGE analysis, we find that capital owners and high-income households are more strongly affected in the short-term, whereas low-income households suffer relatively more from increased price levels and capital scarcity in the long-term. Furthermore, all income quartiles, except for the highest one, are more strongly affected by a reduction of the provision of public services than by changes in private consumption possibilities, highlighting the pressures on public budgets in the aftermath of a disaster. Moreover, wages react more strongly to flood events than capital rents, which results in an indirect risk for the public budget, as labor tax income constitutes a major source of public income. Consequently, also sectors in the public domain are severely affected by floods. Indirect sectoral risk can be measured as lost sectoral GVA relative to the sectoral direct capital damage. Besides publicly provided goods and services, this indirect risk is particularly high for sectors producing goods and services for the final demand. Using the ABM we find that that disasters do not always have necessarily a negative impact on economic growth; however, very extreme disasters have pronouncedly negative economic effects immediately after the event and in the long-term. Similarly to the results of the CGE model, using the ABM we find that disaster losses also differ substantially across industries and economic sectors. It should be noted that we only looked at single extreme events and neglected compound and multi-risk situations, and therefore, our analysis in regards to direct and indirect risk represents a lower bound.

Such information has important consequences for possible risk management and policy strategies, for example, focusing on specific subgroups of the economy, which are usually the most vulnerable to such events to recover quickly. The relative GVA measure also provides a first proxy how direct and indirect losses are related and therefore also provides new ways forward how to manage risk, for example, focusing on the interconnectedness of the sectors and demand agents within risk-layers of indirect risk (Hochrainer-Stigler & Reiter, 2021). By using the here presented (very different) modeling setups, it is possible to better understand what kind of economic dynamics could be, in principle, be expected and therefore develop robust strategies to manage indirect risks.

4.2 | Discussion

Our multi-model approach highlights an important source of (economic) model uncertainty, particularly concerning the assumption of whether the economy is supply or demand driven (see e.g., Bachner et al., 2020 for an in-depth discussion). A supply driven model, such as a CGE model in its default setup, assumes that all production factors are used optimally and that there are no idle physical production capacities. This implies that any additional activity, such as the reconstruction of the capital stock after a damage event, has to be compensated by a reduction of other activities elsewhere in the economy. This in turn means that reconstruction does not work as a kind of economic stimulator but is rather neutral (or negative) to GDP, as reconstruction crowds out otherwise (more) productive investment and capital stock accumulation. Such an economic state would mirror the conditions of an economic boom phase, where the economy runs at its upper production limit, or a state of skill shortage. On the contrary, demand driven models, such as IO models and New-Keynesian models assume non-optimality and frictions, implying that the economy can grow by targeted demand stimulus, for example, by reconstruction. Put differently, such models assume production capacities to be idle, which can be activated by increased demand (e.g., financed by public debt), for example, a situation that occurs during a recession. Although ABMs typically assume bounded rationality and frictions, they neither classify as purely demand-driven nor purely supply-driven. What sets off ABMs from other models is their ability to explicitly model microlevel behavior and heterogeneity as well as to capture nonlinearities. Explicitly modeling the microlevel behavior of heterogeneous agents allows for studying indirect or second-order effects from the adjustment behavior in response to flood damages on the supply and demand of goods and services, the demand of labor, and their interactions. Nonlinearities emerge via market friction in the ABM and cause supply chain disruptions that reduce production capacities. In the here presented analysis, these properties of the ABM result in qualitatively different results when comparing the most extreme event to less severe scenarios, which we would not expect from standard IO models. Specifically, we observe that very extreme events do not stimulate the economy but rather reduce GDP growth in the medium- and long-term. Contrary, the standard IO model would rather increase demand and thus GDP.

Indeed, when comparing the two model classes at hand, they have their unique strengths and weaknesses, and one could think of the best purpose of their application. It becomes evident that the different models are suited for analyses of different time horizons. The ABM, as used here, is best suited to describe short to medium-term effects, that is, effects over 1–5 years (divided into annual quarters) as it is calibrated to rather short-term behavior and expectations of agents (behavioral heuristics). The CGE model assumes long-term macroeconomic balances, constraints, and equilibria and is therefore best used to study the long-term effects of a system intervention, or—alternatively—in the context of phases of economic boom, with physical supply constraints. The direct comparison of model results is thus of limited meaningfulness in terms of plain numbers, nevertheless we reveal that there is large uncertainty at the science-policy interface, particularly with respect to translational uncertainty, which "results from scientific findings that are incomplete or conflicting, so that they can be invoked to support divergent policy positions" (Kunreuther et al., 2014, p. 178). We thus emphasize that model results always need to be communicated in the right context and together with the key assumptions.

Summarizing, large uncertainties exist due to key assumptions of the models employed. We especially identified the state of the economy as well as the time-horizon for estimating indirect risk as yardsticks to decide when and how to use the different models. However, due to the fundamental assumptions of possible interactions a toolbox-based approach may serve best to support decision making as has been called for within so-called iterative approaches lately within systemic risk research (Sillmann et al., 2022), climate change research (IPCC, 2022), and extreme events research (Jacobzone et al., 2020).

The models employed are assuming quite different behavior of economic agents and responses to flood events. They have their own strengths but also weakness which can be compensated by the other model. However, to address model uncertainty, further modeling extensions seem worth exploring. In the CGE model, the possibility to finance reconstruction via debt (even though the capacity constraints might not be of financial but rather of physical nature, e.g., due to certain skill shortages). Further, the CGE model assumes that reconstruction in all scenarios can be completed within 1 year, which might not be the case for very extreme events. More stringent supply constraints might be an extension, worth exploring in the ABM.

With a better understanding of how indirect risks emerge, we suggest that in a next step concrete indirect risk management options and measures should be introduced into such modeling setups. This is again very case specific but can be related in a more general context to the idea of connectedness as an indicator for cascading risks that can be related to risk-layering such as usually done in insurance or direct risk applications (see Hochrainer-Stigler & Reiter, 2021 for a recent review).

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CONFLICT OF INTEREST STATEMENT

There are no conflict of interests to declare.

ORCID

Gabriel Bachner https://orcid.org/0000-0003-2025-0747

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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