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Report

Revealing the indirect risks of flood events:

A multi-model assessment for Austria*

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Abstract

Flood events and the associated damages trigger direct as well as indirect effects due to economy-wide linkages. Hence, flood events pose indirect risks to complex socio-economic systems and their individual agents. Despite their increasing importance in the light of ongoing climate change impacts, such indirect risks are not well understood. Using a set of three different economy-wide models – an input output model, a computable general equilibrium (CGE) model and an agent-based model – we reveal and study indirect risks of flood events for the case of Austria. The three models are fed with high resolution data on sector-specific capital stock damages, which is a major improvement with respect to existing approaches in disaster and climate change impact assessment. We find that indirect risks are very high for most economic sectors and that only the minority of sectors can gain from flood events. Furthermore, on the side of private households we find that floods pose a risk in terms of unequal distributional effects, since capital rents tend to increase while wages tend to decrease in the aftermath of a flood, leading to a re-distribution of income from high- to low-income households. The study thus offers highly relevant leverage points for indirect risk management options in Austria. The used methodologies can be transferred to other regions.

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Introduction

Indirect risks due to natural disasters, for example losses due to business interruption or an increase of indebtedness, and associated climate change impacts are a growing concern for many risk bearers, including the private sector as well as governments, around the world. For example, the recent Global Assessment Reports (UNISDR, 2013, 2015, 2017) issued a stark warning that economic losses linked to disasters are "out of control" and will continue to escalate unless investment in risk reduction is significantly increased and disaster risk management becomes a core part of investment strategies. Moreover, the need to proactively redistribute the growth in asset exposure and to plan for disaster events is becoming increasingly prominent in the discussion on disaster risk management and climate change (IPCC, 2012; UNISDR, 2015; World Economic Forum, 2014).

The paradigm shift toward demand for a more proactive and risk-based approach can be partially attributed to disaster risk being increasingly recognized as a major challenge to economic growth and overall societal well-being in both developing and developed world regions (Uitto & Shaw, 2016). In the Austrian National Climate Change Adaptation Strategy, risk-based approaches are also recommended in many fields of activity, most notably catastrophe management (BMNT, 2017a, 2017b). Especially in highly developed countries, a shift in the disaster risk management perspective can be recently observed with respect to direct and indirect losses. Indirect losses are the flow-on effects from direct losses, such as transport disruptions or business interruptions (Hochrainer-Stigler et al., 2018) and it has been shown that they are significant and can be even larger than the direct losses (Bachner, 2017; Hallegatte et al., 2007). This is particularly the case for industrialized countries, as they are characterized by a high degree of specialization and strong inter-sectoral linkages. Hence, the economy-wide view is becoming more important, which includes the indirect losses emerging from these economy-wide linkages (capturing the total losses of direct and indirect effects). For example, the extreme flood events in 2002 in Austria caused production losses of about 200 million Euro alone (total costs were estimated to be 3.1 billion Euro, (ZENAR & BMLFUW, 2003)). To tackle these indirect risks, the government is often seen, at least implicitly, as being responsible for keeping indirect losses as low as possible and/or to re-distribute them (Hochrainer-Stigler et al., 2018).

Given this shift to an economy-wide view, a significant shift from a risk management perspective also needs to be undertaken, namely, to ask how indirect losses due to natural hazard risks can be decreased within a highly interlinked and complex system such as the economy of a country like Austria. In this report we thus study potential indirect risks from flood events in Austria, using three different modelling approaches: an Input Output (IO) model, a Computable General Equilibrium (CGE) model as well as an Agent Based model (ABM). The general target from this multi-model approach is twofold: First, to learn about and reveal indirect risks by using the strengths of different modelling approaches. Second, to study model uncertainty and model ambiguity at the science policy interface by comparing model results which may feed into policy makers' decisions.

Regarding the latter, we especially focus and expand the idea of risk-layers to also include indirect risks and adapted the framework accordingly. The risk-layer approach for indirect risk will be explained in detail in the WP3 report. In short, loss distributions for direct risk can be used within a risk-layer approach to

determine generic options to manage such risks, including risk reduction and risk financing instruments. For indirect risks, however, the connections and dependencies are the primary focal point, especially in regards to elements in a system (such as the economy) that are too big to fail, too interconnected to fail as well as keystone species. Such elements (or agents) can operate on different scales, e.g. the individual level, regional level or country level, or they can also constitute specific sectors. We use different return period losses for direct risk based on a damage scenario generator approach, which is used as an input to the different models to estimate indirect effects and determine most important sectors and agents.
Our report is organized as follows. Section 2 starts with a detailed description of the damage scenario generator as well as the three modelling approaches used. Afterwards, section 3 presents the results and important findings for each model separately. After that, section 4 compares and discuss the results and finally, section 5 ends with a conclusion and outlook to the work which will be done within WP3.

1. Methodology and models

1.1. General description of methodology

To assess the indirect risks of flood events, we link the three macroeconomic models, the IO model, the COIN CGE model (Bachner, 2017; Mayer et al., 2021; Steininger et al., 2015) and the ABM (Poledna et al., 2020), with the damage scenario generator (described in detail in section 1.2). The damage scenario generator constitutes flood damages for a range of occurrence probabilities and attributes flood-induced losses to the 64 economic sectors of the Austrian economy according to the geospatial distribution of capital owned by non-financial and financial firms and by government entities. Damage data differentiated for economic sectors are then implemented in the three models based on the specific modelling requirements. This implementation technique is described separately for each model in the respective sections 1.3, 1.4 and 1.5 for the IO model, the CGE model and the ABM.
For a selection of occurrence probabilities, i.e. damage scenarios, we systematically compare model results of indirect flood risk. This inter-model comparison allows us to identify model uncertainty as well as model features that drive differences in model outcomes. Eventually we synthesize and discuss strengths and weaknesses of each approach with regard to time horizon and sectorial impact dynamics.

1.2. Damage scenario generator

The challenge of avoiding the underestimation of losses for extremes, which may cause systemic risk and/or large indirect risks we tackled using a so-called copula approach. The approach is especially useful in that it enables an analysis of large-scale extreme events on the country level (Hochrainer-Stigler et al., 2018) which is an essential prerequisite for a probabilistic macroeconomic analysis. Copula approaches are currently seen as most appropriate to include the tail dependent behavior of such events, e.g. a strong correlation of losses between different regions in case of large-scale hazard events (Gaupp et al., 2020; Jongman et al., 2014). As our work specifically looks at very extreme events these two considerations, tail dependence and a risk-based nature, needed to be taken explicitly into account. We therefore used the data and methods as described in Mochizuki et al. (2018) and Schinko et al. (2017), who included tail dependence in their analysis to calculate losses for various return periods for Austria. In what follows, the approach is laid out in more detail.

Estimating the risk of losses due to natural disaster events is done via so-called catastrophe modelling approaches (Grossi et al., 2005; Woo, 2011). There, losses are a function of the natural hazard, the exposure and the physical vulnerability of the exposed elements. As the hazard is represented in probabilistic terms (e.g. the probability of daily rainfall), also the losses are probabilistic and usually represented via a loss distribution (e.g. Figure 1) which gives the relationship between losses and their corresponding probabilities.

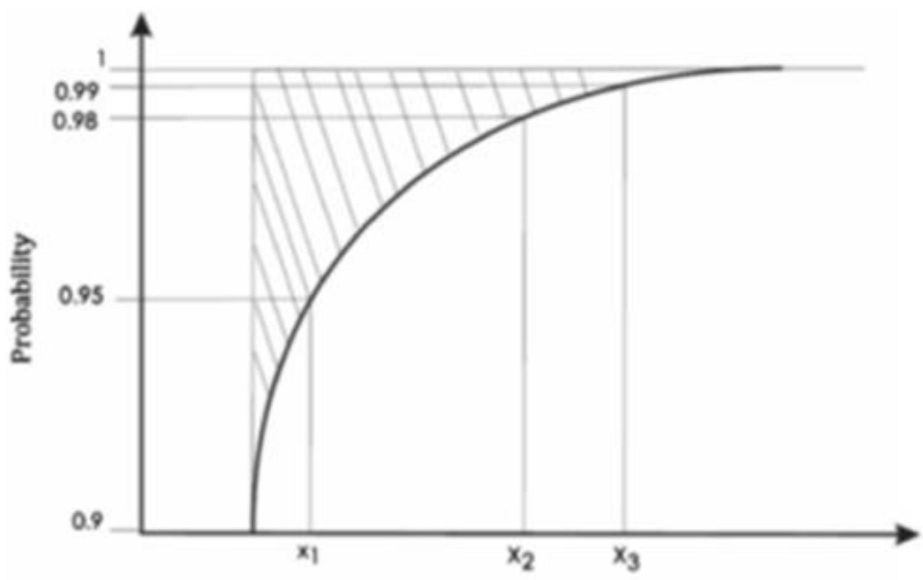

Figure 1: Example of a loss distribution. Based on Hochrainer (2006)

Most modelling approaches calculate such loss distributions on the very local scale, taking the average and summing up these averages over given regions to obtain average losses on larger scales (see for example Lugeri et al., 2010). However, averages can only be used to a limited extent in order to represent extreme risk. What is needed to be obtained on larger scales is also a loss distribution which explicitly considers tail dependence.

In our work the original input for losses on the local level came from Jongman et al. (2014). Current hazards as well as climate simulations used in this study were obtained from the EU FP6 ENSEMBLES project (http://www.ensembles-eu.org/). These simulations constitute a large high-resolution (ca. 25 km x 25 km) ensemble of climate simulations for Europe. In total, 12 climate simulations derived from a combination of 4 GCMs and 7 RCMs, and covering the period 1961-2100 at a daily time step and forced by the SRES-A1B scenario, were used. Afterwards a 5 km x 5 km grid resolution for LISFLOOD (a hydrological based flood model) was applied with a daily time step for the period 1961-2100. LISFLOOD simulates water volumes along river channels as primary output. However, the model also provides river water levels (relative to channel bottom) estimated from the simulated water volumes and the cross-sectional (wetted) channel area of the river section. Extreme value analysis was employed to obtain discharge and water levels for every river pixel associated with different return periods (2-5-10-20-50-100-250-500 years). More specially, a Gumbel distribution was fitted to the 30 annual maxima values defined within 4 time windows (1961-

1990, 1981-2010, 2011-2040 and 2041-2070), which were interpolated into a continuous series for the period 2000 – 2050. For each of these time windows, 8 return periods were estimated. Hazard only affect exposed assets which needed to be assessed as well.

Exposure was measured based on the land use classification of CORINE Land Cover 2006 and country-specific depth-damage functions for different land use classes. For future exposure, the spatial distribution of the exposed assets remained fixed due to the absence of consistent land use projections. A scaling factor reflecting the projected changes in GDP for the A1B scenario was used to account for changes in the value of exposed assets. The loss distribution results on the local scale are held in terms of constant 2006 prices for the time periods considered. Flood models usually do not incorporate protection standards in their results and therefore likely overestimate losses, especially for more frequent events. Therefore, protection standards were included based on the methodology explained in Jongman et al. (2014) in the case for Austria. The specific flood protection standards were defined as the minimum statistical probability discharge that leads to flooding and taken from the Flopros dataset (Scussolini et al., 2016). Vulnerability functions for each of the land class cover types were used to relate hazard intensity with exposure losses (for a discussion see Rojas et al. (2013). As a final outcome, loss distributions in the form of 8 annual loss return periods were estimated.

To upscale the loss distributions from the very local up to the country level, a copula approach was developed (Hochrainer-Stigler et al., 2014). The details of the copula methodology and a general algorithm to perform such coupling can be found in Timonina et al. (2015). In the classic sense, copulas are used for modeling multivariate distributions of continuous random variables. The copula model separates the marginal distributions (e.g. individual risk in the form of a probability distribution) and the structure of dependencies. The method goes back to Sklar's theorem (1959), which states that the joint distribution function H of any continuous random variables X,Y can be written as H(x,y) = C[FX(x), FY(y)] with marginal probability distributions FX(x) and FY(y) and as the (two-dimensional) copula. There are many different copula types available (Gaussian, Clayton, Gumbel, Frank, Joe -- to mention a few), each describing different types of dependence structures including independence (Hochrainer-Stigler, 2020; McNeil et al., 2015).

The flood loss distribution data on the local and basin scale used from Jongman et al. (2014) as described above was used as the input for upscaling distributions to the country level. The different river basin dependencies in Austria were estimated using different copula types C (e.g. Clayton, Frank or Gumbel) and were built on maximum river discharges for the period 1990-2011 for each basin. The loss distributions from each basin were coupled using the given copulas and a minimax ordering approach to finally derive a loss distribution on the country level. To the authors' best knowledge, there are only two other models currently available for Austria using a copula approach (Prettenthaler et al., 2015; Schinko et al., 2016). Both data and approach as described above was used in Mochizuki et al. (2018) and Schinko et al. (2016) specifically for Austria and were so, too, again in this project. The results formed the basic input for the agent-based modelling approach via a damage scenario generator discussed further down below. Table 1 presents the results for different loss return periods for today, 2030 and 2050

Table 1: Current and future losses (in constant bn 2015 Euros) for different return periods. Source: Based on Mochizuki et al. (2018); Prettenthaler et al. (2015); Schinko et al., (2016)

	Return periods						
Time	**20**	**50**	**100**	**250**	**500**	**1000**	**AAL**

2015	0.933	2.878	7.749	12.797	15.553	17.349	0.258
2030	1.309	3.940	10.724	17.572	20.812	23.741	0.764
2050	1.909	5.809	15.468	24.911	29.584	33.814	1.101

Due to the availability of such loss distribution, specific loss events can be looked at and a damage scenario generator can be built to include also multiple events over the selected time period. As a starting point 10 selected scenarios were looked at which span a 10-year-period. In more detail, the first scenario represents the baseline respective no event scenario, the next three scenarios (2-4) look at different effects due to different loss magnitudes (respective 20, 100 and 1000 year loss event), the next three (5-7) scenarios look at two consecutive events over a short time period, the final three scenarios (8-10) look at two consecutive events with a longer time period in between.

Table 2: Selected Scenarios based on the Damage Scenario Generator. Total losses on the country-level in constant 2015 million € for the 2015 situation. Note scenarios 2, 3, and 4 are the 20, 100 and 1000 year event loss, respectively.

Year/ Scenario	1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	0	0	0	0	0	0
2	932	0	0	0	0	0	0	0	0	0
3	7748	0	0	0	0	0	0	0	0	0
4	17349	0	0	0	0	0	0	0	0	0
5	932	0	0	932	0	0	0	0	0	0
6	7748	0	0	7748	0	0	0	0	0	0
7	17349	0	0	17349	0	0	0	0	0	0
8	932	0	0	0	0	0	0	932	0	0
9	7748	0	0	0	0	0	0	7748	0	0
10	17349	0	0	0	0	0	0	17349	0	0

Additionally, we included some very large scale disruptions to see the behavior of the economic repercussions and how the dynamics would eventually differ. In total 4 different so-called Armageddon Scenarios (names because of there extreme high loss potentials) were created based on different assumptions (see Table 3).

Table 3: Selected extreme (“Armageddon”) scenarios

	% of capital stock destroyed	characterization
Armageddon Scenario I	3	1000-year event in all basins simultaneously
Armageddon Scenario II	5	Selected Scenario for Interest
Armageddon Scenario III	17	Half of total exposed assets destroyed
Armageddon Scenario IV	34	Total of total exposed assets destroyed

The second main challenge in this task was to relate the country losses to individuals on a very fine granular scale and according to the specific sectors. The LISFLOOD model used calculated damages based on the so called CORINE Land Cover approach, where each area of a land was determined according to specific land classes. These classes were related to stage damage functions for flood events and losses were calculated accordingly (see Lugeri et al. (2010) for a detailed discussion of this approach). In a first setting it was tried to relate the land cover classes to the specific sectors needed for the economic models, however, it was found out that not all classes can be attributed solely to one sector and many sectors were not able to be included at all. After many more testing it was decided that a different approach has to be adopted here to be able to distribute the losses in the necessary detail.

We finally determined the distribution of losses over all sectors by overlaying flood hazard zone maps based on the highly detailed HORA zoning system and the geospatial distribution of capital according to institutional and industry sectors which was available for all assets in Austria (an unique feature). We then attributed the losses to all 64 industry sectors according to the geospatial distribution of capital owned by non-financial and financial firms and by government entities over these sectors. As a final outcome we were able to distribute large-scale flood losses such as in the table above probabilistically on a very granular scale and use this as an input for WPs 2 and 3. We conclude that state-of-the-art approaches for climate risk management of direct risks are using probabilistic approaches (IPCC, 2012) and the assessment and management of indirect risks within complex system (such as country scale economies) should therefore be able to be conducted in the same way for other purposes (see WP3). Depending on the impact of a flood hazard event and the corresponding losses across heterogeneous agents, different indirect effects emerge as will be discussed in section 2.

The third and last challenge was to relate the losses in terms of total capital stock. This was needed as for the different models some slightly different capital stocks had to be assumed due to calibration purposes. We used the total capital stock at risk based on the Corina Land Cover approach from Lugeri et al. (2010). In more detail, within Braeuninger et al. (2011) as well as (BMVIT, 2009) a comparison of different total capital stock at risk as well as exposed capital stock at risk for different direct risk models was presented and used as an input for determining the losses as percentage of total capital stock which was estimated to be 1107 billion Euros (in constant 2015 currency units).

Summarizing our approach, based on a copula model we determined country scale probabilistic losses due to flood events, used a highly detailed exposure and hazard mapping approach to relate exposed assets to flood events, which was subsequently used to distribute total losses to the individual sectors. Due to a lack of information about the future set-up of the economy, changes in risk due to climate change are indicated through changes in the return period compared to the baseline case. From a risk-layer approach this would mean that future risks may transit from one risk-layer to another which has consequences for risk management strategies (see WP 3).

1.3. Input Output Model

1.3.1. Input Output Model of the Austrian economy

One of the main benefits of Input-Output models (IO Models) is the fact that they offer linearity as well as a simple way of outlining inter-industry linkages and demand structures, usually by imposing specific structural constraints. Furthermore, the empirical construction of IO datasets is supported in many countries through the development of industry classification standards such as ISIC, JSIC and NACE which is used here as well. For a comprehensive review of current IO models for disaster risk analysis we refer to Galbusera & Giannopoulos (2018) and we discuss the classic Leontief based approach also used here in more detail next.

Recall, an IO Table consists of 3 matrices:

- The interrelation (square) matrix Z of size [n by n],
- the external input matrix EI of size [5 by n],
- the external output matrix EO of size [n by 4].

As data basis we will used the 2015 IO-table issued by Statistics Austria. Here n, the number of industry sectors, was n=62 (according to the CPA-classification of products by activity from EUROSTAT with 64 categories - the last one was void and L67 and L68 were collapsed to sector L). Note, the element Z(i,j) of matrix Z contains the total payments industry sector i has paid to industry sector j within the reported year (here 2017). The 5 rows of the external input matrix EI are Imports, Taxes (minus subsidies), Wages, Capital used, and Surplus. The 4 columns of the external output matrix EO are Consumption private, Consumption public, Capital formation and Exports. The 62 economic sectors of the IO model are given in Table 4.

Table 4: Sectors of the Input Output Model

	NACE code	**Description**
1	A1	Products of agriculture, hunting and related services
2	A2	Products of forestry, logging and related services
3	A3	Fish and other fishing products, aquaculture products, support services to fishing
4	B	mining and quarrying
5	C10-12	food products, beverages and tobacco products
6	C13-15	textiles, wearing apparel and leather products
7	C16	Wood and of products of wood and cork, except furniture, articles of straw and plaiting materials
8	C17	paper and paper products
9	C18	Printing and recording services
10	C19	Coke and refined petroleum products
11	C20	Chemicals and chemical products

	NACE code	Description
12	C21	Basic pharmaceutical products and pharmaceutical preparations
13	C22	Rubber and plastics products
14	C23	Other non-metallic mineral products
15	C24	Basic metals
16	C25	Fabricated metal products, except machinery and equipment
17	C26	Computer, electronic and optical products
18	C27	Electrical equipment
19	C28	Machinery and equipment n.e.c.
20	C29	Motor vehicles, trailers and semi-trailers
21	C30	Other transport equipment
22	C31-32	Furniture, other manufactured goods
23	C33	Repair and installation services of machinery and equipment
24	D	Electricity, gas, steam and air-conditioning
25	E36	Natural water, water treatment and supply services
26	E37-39	Sewerage, waste collection, treatment and disposal activities, materials recovery, remediation activities and other waste management services
27	F	Constructions and construction works
28	G45	Wholesale and retail trade and repair services of motor vehicles and motorcycles
29	G46	Wholesale trade services, except of motor vehicles and motorcycles
30	G47	Retail trade services, except of motor vehicles and motorcycles
31	H49	Land transport services and transport services via pipelines
32	H50	Water transport services
33	H51	Air transport services
34	H52	Warehousing and support services for transportation
35	H53	Postal and courier services
36	I	Accommodation and food services
37	J58	Publishing services
38	J59-60	Motion picture, video and television programme production services, sound recording and music publishing, programming and broadcasting services
39	J61	Telecommunications services
40	J62-63	Computer programming, consultancy and related services, information services
41	K64	Financial services, except insurance and pension funding
42	K65	Insurance, reinsurance and pension funding services, except compulsory social security
43	K66	Services auxiliary to financial services and insurance services
44	L67-68	Real estate services excluding imputed rents and imputed rents of owner-occupied dwellings
45	M69-70	Legal and accounting services, services of head offices, management consulting services

	NACE code	Description
46	M71	Architectural and engineering services, technical testing and analysis services
47	M72	Scientific research and development services
48	M73	Advertising and market research services
49	M74-75	Other professional, scientific and technical services, veterinary services
50	N77	Rental and leasing services
51	N79	Employment services
52	N79	Travel agency, tour operator and other reservation services and related services
53	N80-82	Security and investigation services, services to buildings and landscape, office administrative, office support and other business support services
54	O	Public administration and defence services, compulsory social security services
55	P	Education services
56	Q86	Human health services
57	Q87-88	Social work services
58	R90-92	Creative, arts and entertainment services, library, archive, museum and other cultural services, gambling and betting services
59	R93	Sporting services and amusement and recreation services
60	S94	Services furnished by membership organisations
61	S95	Repair services of computers and personal and household goods
62	S96	Other personal services

The total payments (input) of industry sector j in the reported year appear as the j-th column of the matrices Z and EI. The total input of sector j (total costs including the Surplus):

$$\text{Total.Input}(j) = \underbrace{\sum_i Z(i,j)}_{internalInput} + \underbrace{\text{Imp(j)} + \text{Tax(j)} + \text{Wag(j)} + \text{Cap used(j)} + \text{Splus(j)}}_{externalInput}$$

In short:

$$I_{tot} = \mathbb{1}_n' Z + I_{ext}$$

The revenues (output) of industry sector i appear as the i-st row of the matrices Z and EO. The total output of industry sector i (total revenues) is

$$\text{Total.Output(i)} = \underbrace{\sum_j Z(i,j)}_{internalOutput} + \underbrace{\text{Cons}_{publ}\text{ (i)} + \text{Cons}_{priv}\text{(i)} + \text{Cap form.(i)} + \text{Exp(i)}}_{externalOutput}$$

In short:

$$O_{tot} = Z\mathbb{1}_n + O_{ext}$$

The fundamental macroeconomic balance equation states that for each sector

$$I'_{tot} = O_{tot}$$

For further analysis, A, the matrix of technological coefficients is introduced

$$A = Z[diag(I_{tot})]^{-1}$$

Then

$$I'_{tot} = O_{tot} = A \ diag(I_{tot})'\mathbb{1}_n + O_{ext} = AI'_{tot} + O_{ext}$$

From which one gets

$$(E_n - A)I'_{tot} = O_{ext}$$

Or,

$$I'_{tot} = LO_{ext}$$

Where L is the inverse of (I-A) which I being the identity matrix.

$$L = (E_n - A)^{-1}$$

Here L is the famous Leontief inverse. A similar analysis can be made for the transpose of Z leading to the Ghosh Inverse. The structure of an IO-model can be schematically represented as in Figure 2.

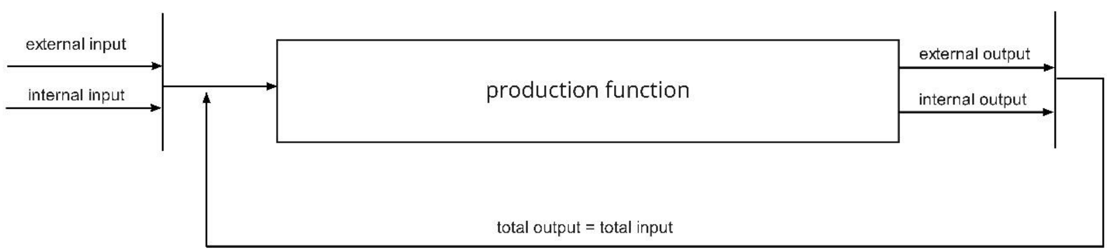

Figure 2: Schematic representation of an IO model

Using the matrix L, one may calculate the needed relative change of the input j given that the output i changes by 1 percent. Denoting this percentage by C_{ij}, one may visualize this 62 by 62 matrix in a square scheme, where the size of the element at position i,j is proportional to C_{ij}.

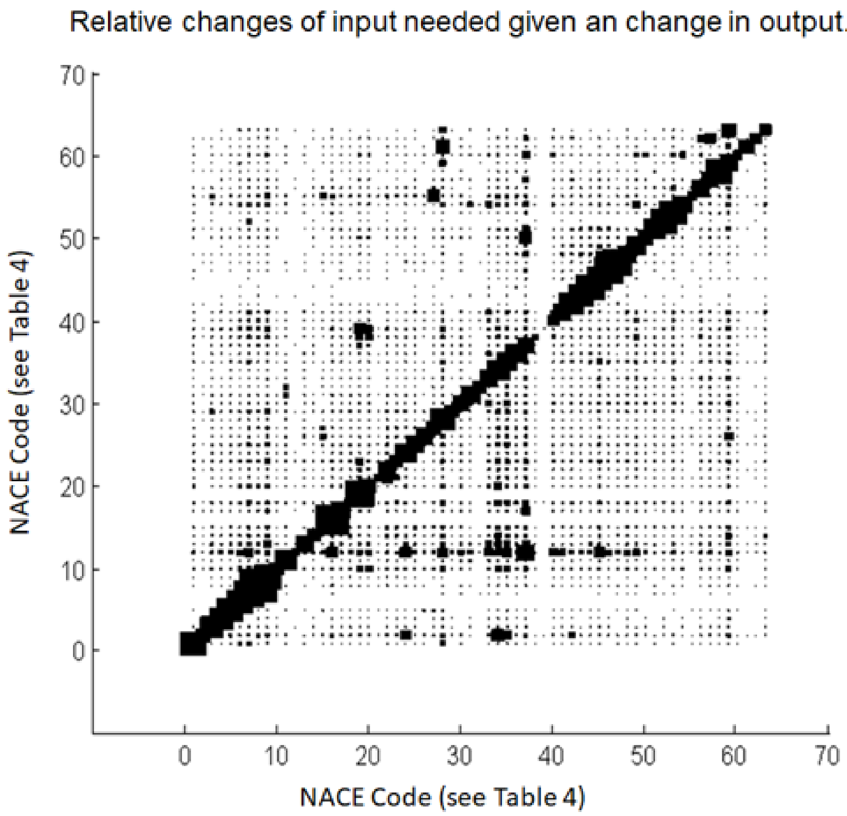

Figure 3: Relative change of the input j (y axis) given that the output i (x axis) changes by 1 percent.

1.3.2. Production functions

Production functions relate the input of an economic system to the output. Notice that in IO models part of the outputs are also inputs such that there is a feedback loop instead of a simple functional relationship. For the internal part of the model, the production function f maps the 62-vector of inputs to the 62-vector of outputs. The classical Leontief model assumes linearity, i.e. assumes that the relationship is (with x as input and y as output) y=f(x)=Ax, leading to the classical relationship:

Total Input = L * External Output or

$$x_{tot} = L y_{ext}$$

Where A and L were explained in section 2.3.1. However, linear production functions imply total substitut-ability, meaning that e.g. a car can be produced without any glass if only one has an unlimited input of metal. In order to account for limitations in substitutability Leontief has also considered another production function, namely strict non-substitution We have extended the classical Leontief function to a more general function class, which contains the Leontief function as a special case:

$$y = A \cdot x \cdot \min(\min_j \frac{1}{b} \frac{x_j}{x_j^{min}}, 1)$$

Here xjmin are the minimal amounts of inputs of sector i to produce one unit of product (this amount assumed to be is independent of what is produced). If b is set to 1, then the classical Leontief production no-substitution function is reproduced. If b is set to 0, the linear production function is obtained. For the here presented analysis we set b=1; i.e. we do not allow for substitution in production.

We follow a output shock approach and increase the demand of input accordingly due to the destruction of capital. Furthermore, we are able to calculate the relative changes according to the Leontief model.

1.4. Computable General Equilibrium model

1.4.1. General description of computable general equilibrium models

In general, Computable General Equilibrium (CGE) models explore the economy-wide and indirect effects of localized "shocks" within the economic system, for instance, from the introduction of policies or weather related shocks. Since a CGE model captures all economic sectors, their cross-sectoral integration (via input-output connections) as well as final demand, it is "general" in scope. Assuming profit (utility) maximization of producers (consumers) and using production (utility) functions calibrated to observed elasticities of substitution, CGE models are based on micro-economic theory and empirical observations.

The main idea behind CGE models is, that all markets are cleared simultaneously, meaning that supply equals demand for all goods, services and factors. This "general equilibrium" depicts the economy as a flow equilibrium (usually on an annual basis) which can then be disturbed in a counterfactual experiment by an intervention. After such an intervention the main drivers of system change are relative prices and the associated demand responses. Once an exogenous intervention takes place, relative prices change; e.g. the price of a product might increase due to a new tax that is introduced. In turn, economic agents (producers and consumers) react to this change in relative prices by changing their demand patterns (lower demand for more expensive products and higher demand for the now relative cheaper products), however within their technological and resource/budget constraints. This first round effect of reactions again triggers second round effects etc. Ultimately this adjustment process continues until a new equilibrium is reached in which all markets are cleared again, but now at different prices and quantities than before. By comparing the new equilibrium to the old one, one can isolate the effects of the exogenous intervention. This comparison of two equilibria is referred to as "comparative static" analysis. When connecting annual equilibria via capital accumulation (investment in period t determines the capital stock and the equilibrium in period t+1) we speak of a "recursive dynamic" approach that is able to project the development of the economy into the future. Usually this is done by also including other assumptions of expected socio-economic developments (e.g. population growth or technological change). One can then compare different pathways into the future to each other rather than single years.

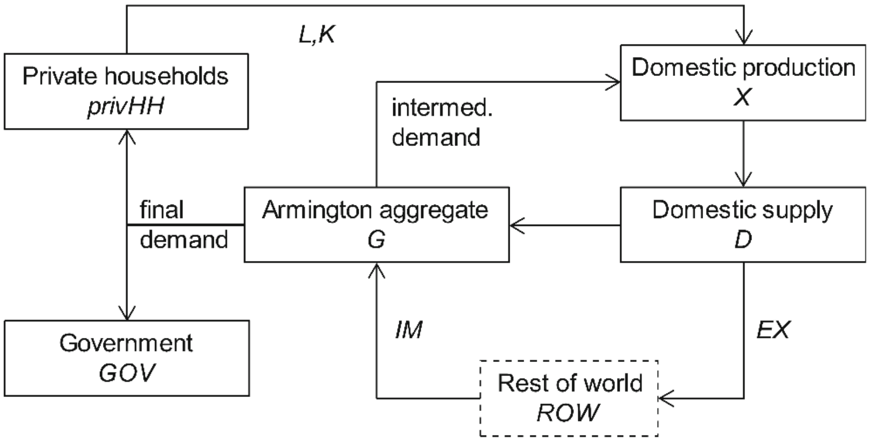

Figure 4: Conceptual overview of a CGE model (source: Bachner et al., 2015, p. 109)

Figure 4 illustrates the conceptual framework of a CGE model. Private households are endowed with the production factors capital (K) and labor (L), which are provided via factor markets to domestic production (X). Together with inputs from other sectors (intermediate demand), domestic sectors generate output, which is either supplied to foreign countries as exports (EX), or remaining in the domestic market. The so called "Armington aggregate", combines imports and domestic products, which are then supplied at the domestic market for either final demand (private and public consumption as well as investments) or intermediate demand. The system is thus closed and driven by factor supply.

The idea of general equilibrium is one of long-term character, which implies that production capacities are fully/optimally utilized (i.e. the economy is supply-side constrained) and that there is neither excess-supply nor excess-demand. These assumption can be relaxed however, e.g. by introducing market friction such as minimum wages and unemployment on the labor market.

The WEGDYN-AT model, which is used in the following analysis, is a recursive-dynamic, multi-sector, small-open-economy CGE model calibrated to the Austrian economy. It builds upon the static version of Bachner (2017) but has been enhanced to a recursive-dynamic version as given in Mayer et al. (2021).

We calibrate the model (flow equilibrium of the first year) to a social accounting matrix (SAM) of the year 2014, which is based on an input-output table of 72 NACE-classified economic sectors (Statistics Austria, 2014). Elasticities of substitution are taken from econometric estimates provided in literature (Koesler & Schymura, 2015; Okagawa & Ban, 2008). The model equations represent a mixed complementary problem and are written in the MPSGE language using the programme GAMS. We solve the model using the PATH solver (Ferris & Munson, 2000).

1.4.2. Supply side

The WEGDYN-AT model features a detailed level of sectoral disaggregation with 74 production sectors (Table 5 and Table A 1). Special emphasis is placed on the energy sector, which is further disaggregated to represent distinct fossil-fueled and renewables-based generation technologies. All producers are assumed to maximize profits in perfectly competitive markets given constraints on the availability of production factors (labor and capital) and thus income.

Table 5: Model sector acronyms and description

Model code	Sector description	Model code	Sector description
AGRI	Agriculture	**TRRE**	Retail trade
FORE	Forestry and logging	**LTRA**	Land transport
FISC	Fish and fishery	**WTRA**	Water transport services
FEXT	Fossil fuel extraction	**ATRA**	Air transport services
MEXT	Other mining and quarrying	**STRA**	Service activities for transport
FOOD	Food products	**POST**	Postal and courier services
BEVE	Beverages and Tobacco	**ACCO**	Accommodation services
TEXT	Textiles	**SPUB**	Publishing activities
CLOT	Wearing apparel	**CINE**	Audio-visual services
LEAT	Leather and related products	**BRDC**	Programming and broadcasting
WOOD	Wood and products of wood and cork	**TELE**	Telecommunication
PAPE	Paper and paper products	**SITC**	Information tech. and communication
PRNT	Printing and recording services	**SFIN**	Financial services
CHEM	Chemicals and chemical products	**INPE**	(Re-)Insurance and pension funding
PHAM	Pharmaceutical products	**SFIO**	Services for financial a. insurance serv.
PLAS	Rubber and plastic products	**REAL**	Real estate services
GLAS	Other non-metallic mineral products	**LEGA**	Legal and accounting services
META	Basic metals	**CNSU**	Management consulting services
MAME	Fabricated metal products	**ARCH**	Architectural and engineering services
MAED	Electronic and optical products	**RADE**	Scientific research and development
MAEL	Electrical equipment	**ADVT**	Advertising and market research
MACA	Machinery and equipment	**FREO**	Other services; veterinary services
MAVE	Motor vehicles	**SRNT**	Rental and leasing services
MAVO	Other transport equipment	**SLAB**	Employment services
MAFU	Furniture	**TRAV**	Travel agency, tour operator and related
MAOT	Other manufactured goods	**SECO**	Other business support services
MARE	Repair and installation of machinery	**PUBL**	Public administration
ELYs	Electricity	**EDUC**	Education services
HEATs	Heating	**HEAL**	Human health services
GAS_MDT	Gas transmission, distribution and trade	**NURS**	Information tech. and communication
WATE	Water treatment and supply	**ARTS**	Financial services
WAST	Waste management a. remediation	**CULT**	(Re-)Insurance and pension funding
BUIL	Buildings and building construction	**GMBL**	Services for financial a. insurance serv.
CIEN	Construction work	**SPOR**	Real estate services
CONT	Specialised construction works	**ASSO**	Legal and accounting services
TRCA	Trade and repair of motor vehicles	**UREP**	Management consulting services
TRWH	Wholesale trade	**SOTH**	Architectural and engineering services
NRGall	All energy sectors combined (ELYs, HEATs, GAS_MDT)		

1.4.3. Demand side

On the final demand side, we differentiate between private and public consumption, investment and exports. All final demand agents are assumed to maximize utility subject to their budget constraint, which is given either by their labor and capital income as well as public transfers (in case of a private household), or by tax revenues (in case of the public household). For private households, we distinguish between twelve representative household groups reflecting income quartiles (from Q1 – lowest income quartile to Q4 – highest income quartile) by residence location (urban, suburban and periphery) in order to be able to analyze distributional effects (see Mayer et al., 2021 for details). As the distributional effects of flood damages are strongly driven by the composition of income and expenditures of private households, we briefly describe how the different household groups differ with respect to their income and expenditure structure.

Regarding income, Figure 5 shows the different sources of income for the twelve private household groups as well as the distribution of income across consumption and savings. The share of labor income declines with an increase in income, while public transfers are a much larger source of income for low(er) income groups. Higher income households have higher shares of factor income and especially of capital income, whereas lower income households are „protected" by transfers. Regarding the expenditures, higher income households have higher savings rates, while lower income households are more depending on consumption.

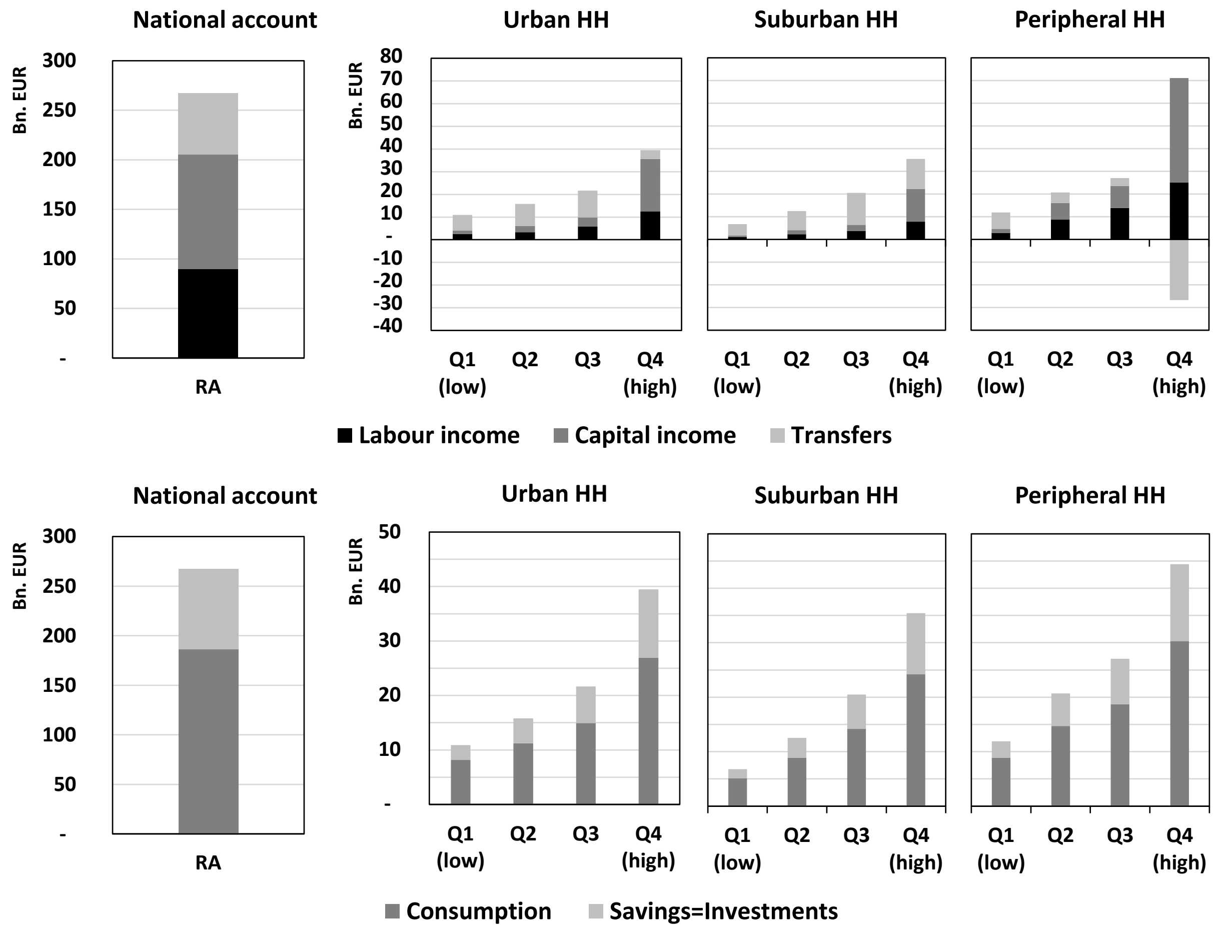

Figure 5: Income source for household groups and consumption vs savings distribution

Regarding the consumption of the different income groups, Figure 6 depicts the shares of income spent on different sectors aggregated to 10 clusters for the twelve household groups. While expenditures for housing constitutes a significant share of income for all income groups, lower income groups spend substantially higher shares of their income on housing. Especially the lowest income quartile (Q1) spends more than a fourth of their income on housing regardless the residence location. For the highest income quartile, this share amounts to 12% in urban and suburban locations and to 10% in the periphery. Lower income groups are therefore more strongly exposed to the flood damages in the housing sector. Also, the share of expenditures for food, beverages and natural resources, for energy and sanitation as well as for transport decreases with increasing income. While these three sector clusters add up to another fourth of expenditures of the lowest income group, it amounts to around 14% for the highest income group. In contrast, expenditure shares for the remaining sector clusters, such as clothing, leisure activities, vehicles, education and health as well as financial services (see Figure 6 for the complete list) increase with increasing income. For example, income spent on accommodation and travel as well as other leisure activities amounts to 15% in urban residence locations and 12% in both suburban and peripheral residence locations for the lowest income quartile. For the highest income quartile, this share rises to 23% in urban residence locations, to 20% in suburban and to 19% in peripheral residence locations. The share of income spent on education and health is around twice as large for the highest income quartile as compared to the lowest income quartile.

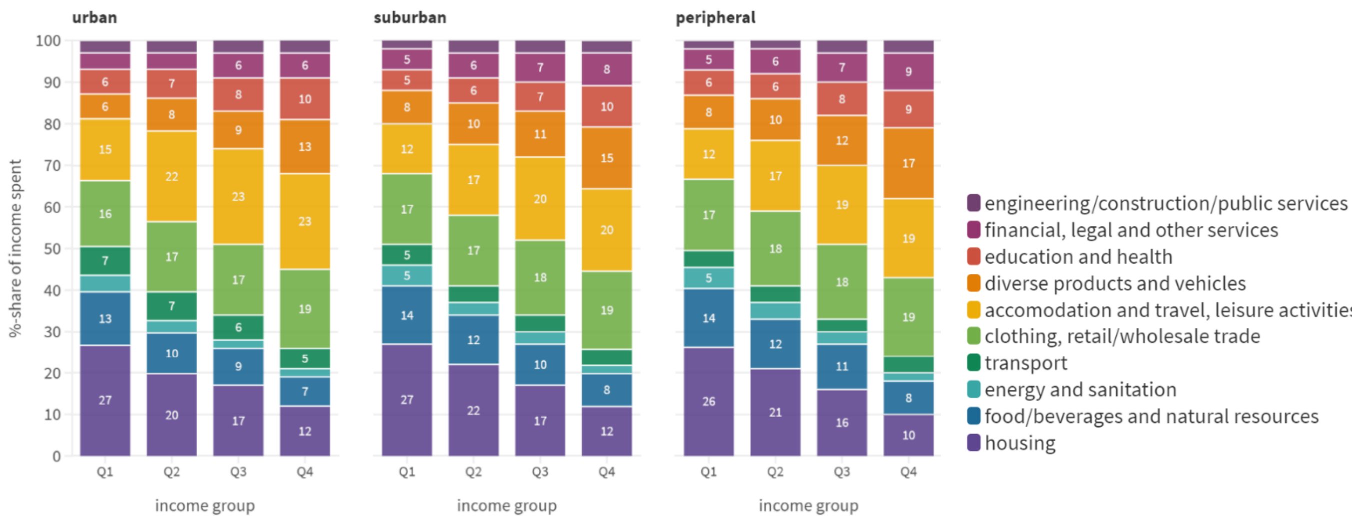

Figure 6: Expenditure structure for private households differentiated for income group and location.

1.4.4. Foreign trade

We model Austria as a small open economy, meaning that Austria is not able to influence world market prices by its trade behavior. In the model other regions than Austria are not modelled explicitly, but foreign trade is accounted via trade flows to and from Austria. For importing foreign goods and services foreign exchange is necessary, which is obtained by exporting goods and services. Foreign trade is implemented according to the Armington assumption (Armington, 1969), meaning that domestically produced goods and imported goods are imperfect substitutes and as such treated differently subject to sectorally differentiated elasticities of substitution. Foreign trade is closed by assuming a fixed current account balance, which grows with GDP. The current account is balanced via net-capital inflows of opposite sign (i.e. the capital account). As numeraire we choose the foreign exchange price level.

1.4.5. Factor markets

In the default version of the WEGDYN-AT model factor markets are cleared, meaning that there is no excess supply of capital or labor. This means that the capital stock runs at full capacity and that there is no unemployment. On the capital market we refine the existing model by differentiating capital stocks across sectors.[†] Thus, each sector has its own capital stock and capital is immobile across sectors. Capital accumulates over time (see section 1.4.6) and since all available capital is used, capital rents (remuneration of the factor capital) are flexible, i.e. they adjust such that the capital market is cleared. As opposed to capital, labor is generic and thus assumed to be perfectly mobile across sectors. Labor supply grows exogenously with working age population. The wage rate (remuneration of the factor labor) is flexible and leads to market clearance on the labor market.

These assumptions for factor markets best represents a situation of economic boom, where there are no idle production capacities. This implies that if some economic activity needs to be increased (e.g. investment) other economic activities are crowded out, since production capacities are scarce. This further means that income (GDP) can not be increased by demand side changes.

1.4.6. Recursive dynamics and investment closure

The WEGDYN-AT CGE model is recursive dynamic model which solves in yearly time steps starting from 2014. It explicitly models the pathway of generic economic development according to a middle of the road scenario. The individual time steps are connected via the following equation of capital accumulation: $KS_{i,t+1} = (KS_{i,t}(1-\delta)) + (I_t\bar{\tau}_i)$. This equation reads as follows. The capital stock (KS) of sector i in the next year period (t+1) is determined by the current year (t) capital stock, minus deprecation according to the depreciation rate (δ), plus current period Investments (I) times the sectoral investment share τ.

The recursive dynamic model specification implicitly assumes myopic behaviour of all economic agents, that is, they do not include future expectations in their decision but optimize within the current period.

The determination of generic investment is as follows: Total economy-wide volume of investment is given by a fixed savings rate (i.e. a fixed share of income is devoted for savings, which is equal to investment). Since capital is sector specific, a heuristic on how much is being invested into which kind of capital stock (of which sector) is needed. This decision is based on sector specific capital rents of the past (previous period), with higher capital rents attracting investors and vice versa. Thus, while having a total investment volume that is determined by a fixed savings rate, the composition of investment (i.e. into which sector's capital stock is being invested), varies subject to sector specific capital rents of the past (see Appendix for details).

1.4.7. Scenarios and Implementation of flood damages

For the macroeconomic analysis of flood damages, we differentiate between two types of scenarios: a baseline scenario and an impact scenario. In the baseline scenario, parameters, such as GDP and labour force, grow according to exogenously determined data for the middle of the road scenario. Production technologies improve by an autonomous energy efficiency improvement (AEEI) indicator and capital develops as described in the previous section based on household-specific saving rates. The baseline scenario

[†] This is done based on capital flows as given by the underlying input output table.

therefore depicts the evolution of the Austrian economy between 2014 and 2025 in annual time steps for a scenario, where no natural disasters or other unscheduled events occur.

In the impact scenario, in addition, flood damages hit the economy in the first year of analysis or repeatedly. To identify the effect on macroeconomic indicators over time, we compare the impact scenario to the baseline scenario for each year. Thereby, we are able to isolate the impact of flood damages in the first year, when the disaster actually occurs, as well as in the following years, when the economy recovers from the initial shock.

In the following, we describe how flood damages generated by the damage scenario generator enter the impact scenario in the CGE model and which mechanisms are thereby initiated. First, flood damages are implemented as a reduction of the sector-specific capital stock. This assumption is based on the determination of damage data in the catastrophe model, that reports damaged capital per economic sector. Flood damages destroy productive capital, i.e. capital that is used as an input factor in sectoral production in the CGE model, which affects production in the year of the shock. However, capital is also accumulated as described in the previous section driving economic growth. Thus, a reduction of capital in one period results in a long-term effect on the economy. To cover both effects, damaged capital directly enters the capital accumulation equation (see below) as a negative component ($D_{i,t}$).

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

This set up leads to a slowing down of the capital accumulation and economic growth as compared to a scenario without flood damages. The extent to which this happens varies with the damage scenarios.

Second, reconstruction activities are implemented via additional forced investments by the private sector. In the CGE framework with no idle production capacities this implies that other economic activity is crowded out, when reconstruction takes place. Specifically, we assume that generic investment and consumption are crowded out by the same percentage (e.g. both by x%), such that the additional investment burden can be financed. Note that the additional investment also builds up capital stock, however, since it partly crowds out generic investment elsewhere in the economy the capital stock does not reach its level as before the flood event takes place. When including reconstruction, capital accumulation is described as follows

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

with $R_{i,t}$ being sectoral reconstruction. In terms of investment volume and reconstruction costs 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 generic investment is crowded out, I is reduced and thus KS is smaller. Reconstruction is mainly covering replacement/repair of buildings, machinery, and vehicles. In addition, we assume that labor costs for clearing up in the aftermath of the event is 10% of the capital damage.

1.5. Agent-Based Model

1.5.1. Description of the agent-based model

In this work, we use an ABM developed by Poledna et al. (2020). This ABM includes all institutional sectors (financial firms, non-financial firms, households, and a general government). The firm sector is composed of 64 industry sectors according to national accounting conventions and the structure of input-output tables.

The data come from national accounts, sector accounts, input-output tables, government statistics, census data, and business demography data. Model parameters are either taken directly from data or are calculated from national accounting identities. For exogenous processes such as imports and exports, parameters are estimated. The model furthermore incorporates all economic activities classified by the European system of accounts, both for producing and distributive transactions. All economic entities, i.e., all juridical and natural persons, are represented by heterogeneous agents. Markets are fully decentralized and characterized by a continuous search and matching process that allows for trade frictions. Agent forecasting behavior is modeled by parameter-free adaptive learning, in which agents estimate the parameters of their model and make forecasts using their estimates, as would econometricians do (Evans & Honkapohja, 2001). For that, we follow the approach of Hommes & Zhu (2014), in which agents learn the optimal parameters of simple parsimonious AR(1) rules. The ABM is validated based on historical data by demonstrating comparable performance to standard DSGE and VAR models.

Following the sectoral accounting conventions of the European System of Accounts (ESA) (Eurostat, 2013), the model economy is structured into six sectors that mirror the structure of institutional sectors as defined by the ESA: (1) non-financial corporations (firms); (2) households; (3) the general government; and (4) financial corporations (banks), including (5) the central bank. These four sectors make up the total domestic economy and interact with (6) the rest of the world (RoW) through imports and exports. Each sector is populated by heterogeneous agents, who represent natural persons or legal entities (corporations, government entities, and institutions). All individual agents have separate balance sheets, depicting assets, liabilities, and ownership structures. The balance sheets of the agents, and the economic flows between them, are set according to data from national accounts.

Along these lines and following the structure of our dataset, the firm sector ((1) non-financial corporations) is made up of 64 industries (NACE/CPA classification by ESA) where each industry produces a perfectly substitutable good. Each firm in the model is part of one industry and produces the industry-specific output by means of labor, capital, and intermediate inputs from other sectors with a fixed coefficients (Leontief) technology. These fixed coefficients are calibrated directly to input-output tables. The firm population of each industry is derived from business demography data, while firm sizes follow a power-law distribution, which approximately corresponds to the firm size distribution in Austria. Heterogeneity in the firm sector is thus achieved by industry-specific production functions and varying firm sizes. Similar to other agents in the model, firms are subject to fundamental uncertainty. This uncertainty specifically relates to their future sales, market prices, the availability of inputs for production, input costs, cash flow, and financing conditions. Based on partial information about their current status quo and its past development, firms have to form expectations to estimate future demand for their products, their future input costs, and their future profit margin. According to these expectations—which are not necessarily realized in the future—firms set prices and quantities. In line with our overall approach to expectation formation, we assume that firms form these expectations using simple AR(1) rules. Output is sold on respective markets characterized by search and matching to households as consumption goods or investment in dwellings and to other firms as intermediate inputs or investment in capital goods, or it is exported. Firm investment is conducted according to the expected wear and tear on capital. Firms are owned by investors (one investor per firm), who receive part of the profits of the firm as dividend income.

(2) Households earn income and consume (and invest) in markets characterized by search and matching processes. Heterogeneity in the household sector is achieved by the distinction into employed (with sector-

specific characteristics), unemployed, investor, and inactive households, with the respective numbers obtained from census data. The source of income is specific for the different household types: employed households supply labor and earn sector-specific wages. Unemployed households are involuntarily idle and receive unemployment benefits, which are a fraction of previous wages. Investor households obtain dividend income from firm ownership. Inactive households do not participate in the labor market and receive social benefits provided by the government. Additional social transfers are distributed equally to all households (e.g., child care payments). All households purchase consumption goods and invest in dwellings which they buy from the firm sector. Due to fundamental uncertainty, households also form AR(1) expectations about the future that are not necessarily realized. Specifically, they estimate inflation using an AR(1) model to calculate their expected net disposable income available for consumption.

The main activities of (3) the general government are consumption on retail markets and the redistribution of income to provide social services and benefits to its citizens. The amount and trend of both government consumption and redistribution are obtained from government statistics. The government collects taxes, distributes social as well as other transfers, and engages in government consumption. Government revenues consist of (1) taxes: on wages (income tax), capital income (income and capital taxes), firm profit income (corporate taxes), household consumption (value-added tax), other products (sector-specific, paid by industry sectors), firm production (sector-specific), as well as on exports and capital formation; (2) social security contributions by employees and employers; and (3) other net transfers such as property income, investment grants, operating surplus, and proceeds from government sales and services. Government expenditures are composed of (1) final government consumption; (2) interest payments on government debt; (3) social benefits other than social benefits in kind; (4) subsidies; and (5) other current expenditures. A government deficit adds to its stock of debt, thus increasing interest payments in the periods thereafter.

The banking sector ((4) financial corporations) obtains deposits from households as well as from firms and provides loans to firms. Interest rates are set by a fixed markup on the policy rate, which is determined according to a Taylor rule. Credit creation is limited by minimum capital requirements, and loan extension is conditional on a maximum leverage of the firm, reflecting the bank's risk assessment of the potential default by its borrower. Bank profits are calculated as the difference between interest payments received on firm loans and deposit interest paid to holders of bank deposits, as well as write-offs due to credit defaults (bad debt). (5) The central bank sets the policy rate according to a generalized Taylor rule based on implicit inflation and growth targets, provides liquidity to the banking system (advances to the bank), and takes deposits from the bank in the form of reserves deposited at the central bank. Furthermore, the central bank purchases external assets (government bonds) and thus acts as a creditor to the government.

To model interactions with (6) the rest of the world, a segment of the firm sector is engaged in import-export activities. As we model a small open economy, whose limited volume of trade does not affect world prices, we obtain trends of exports and imports from exogenous projections based on national accounts.

1.5.2. Implementation of flood damages

We apply the ABM to study indirect economic losses from flood events in Austria. As in Poledna et al. (2018), the damage-scenario generator simulates a shock to individual agents from the ABM, which subsequently alter their behaviour and create higher-order indirect effects over a given period. Figure 7 depicts the basic structure of the ABM and the integration of the damage-scenario generator. After simulating different flood events corresponding to a 100-year, 1000-year, and an extreme event at the beginning of the year 2015, which destroys or damages dwellings, the capital stock of firms, and infrastructure, we study the indirect economic effects of these flood events over the time horizon of five years using the ABM.

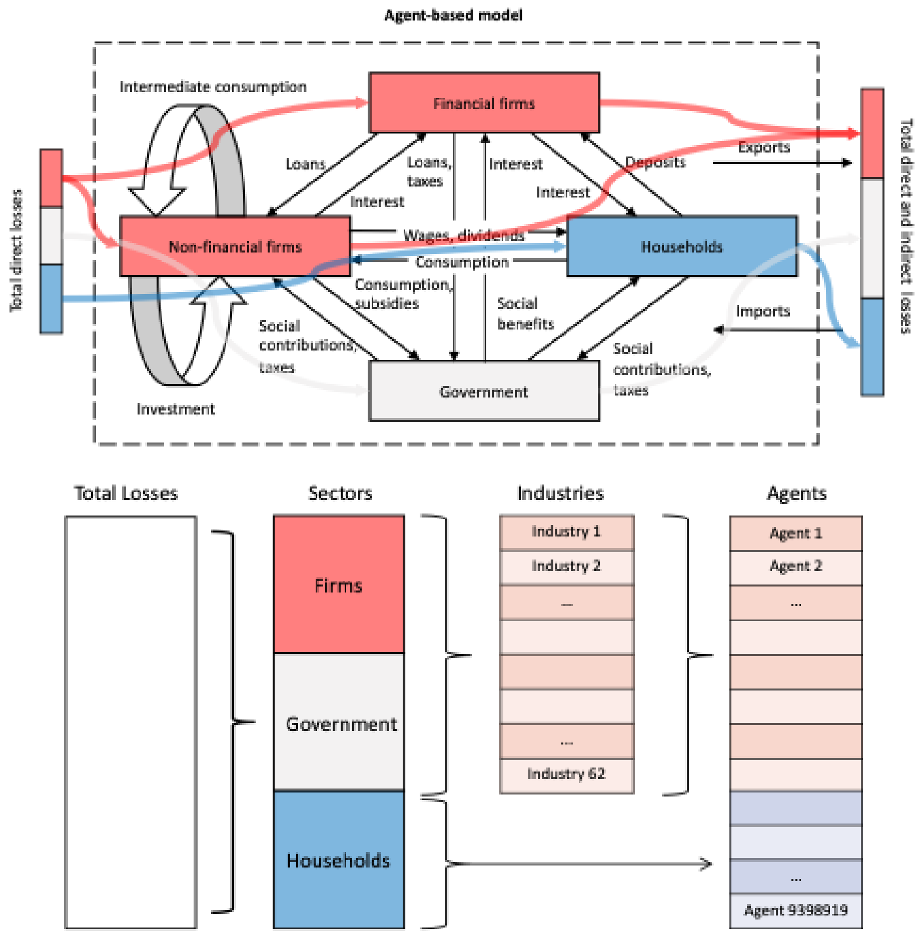

Figure 7: Basic structure of the ABM showing the institutional sectors (households, non-financial and financial firms, and a general government), and their interactions. The stacked bars show an example of the distributions of direct (left) and indirect (right) total losses to the government (white), firms (red), and households (blue). Distribution of total losses to institutional sectors, industry sectors, and individual agents.

2. Individual model results

2.1. Results from the input output model

While the Input-Output model is a flow model, the damage scenario generator generates scenarios of losses of capital stock. The total exposed stock was estimated by 1,007 bn. EUR. The following seven damage scenarios were considered

1. RP20: Return Period 20 years

The distribution of losses among the industry sectors was calculated according to the damage model. The total losses of all sectors together are in this scenario 0.08% of the exposed stock, i.e. 0.81 bn. EUR.

2. RP100: Return Period 100 years

The total losses amount to 0.7% of the exposed stock, I.e. 7.05 bn. EUR.

3. RP1000: Return Period 1,000 years

In this scenario the total losses are 2.57% of the exposed stock, i.e. 25.8 bn. EUR.

4. AG1: Armageddon 1

The following 4 Armageddon scenarios were chosen with no relation to the damage module, they were selected to test the effect of very large losses. The Armageddon 1 losses are 3% of the exposed stock, i.e. 30.2 bn. EUR.

5. AG2: Armageddon 2

Here the total losses are 5% or 50.35 bn. EUR.

6. AG3: Armageddon 3

The third Armageddon scenario affects 17% of the total exposed stock, or 171.2 bn. EUR.

7. AG4: Armageddon 4

In this extremely high scenario 34% of the total exposed stock is lost, i.e. the losses are 342.4 bn. EUR.
In order relate the possible losses in stock to the flow values of an IO-model, we assume that all losses will be compensated within just one year. That is, the necessary output is increased by the money value of the losses in the respective scenario. In other words, demand is increased according to the relative losses in the specific sectors based on the damage scenario generator and we look at increased input needed due to this increased demand.
The one-year recovery might seem as too short, but the relative necessary increases in input calculated below may be halved, if the recovery time is extended to two years. Conversely, the IO-model's output can be used to detect bottlenecks, i.e. by how much a sector's output would need to increase for compensating the damage.
The following figures show the necessary increases in input for each sector (from 1 to 62; see Table 4 for descruptions). The largest increases are indicated for each scenario.

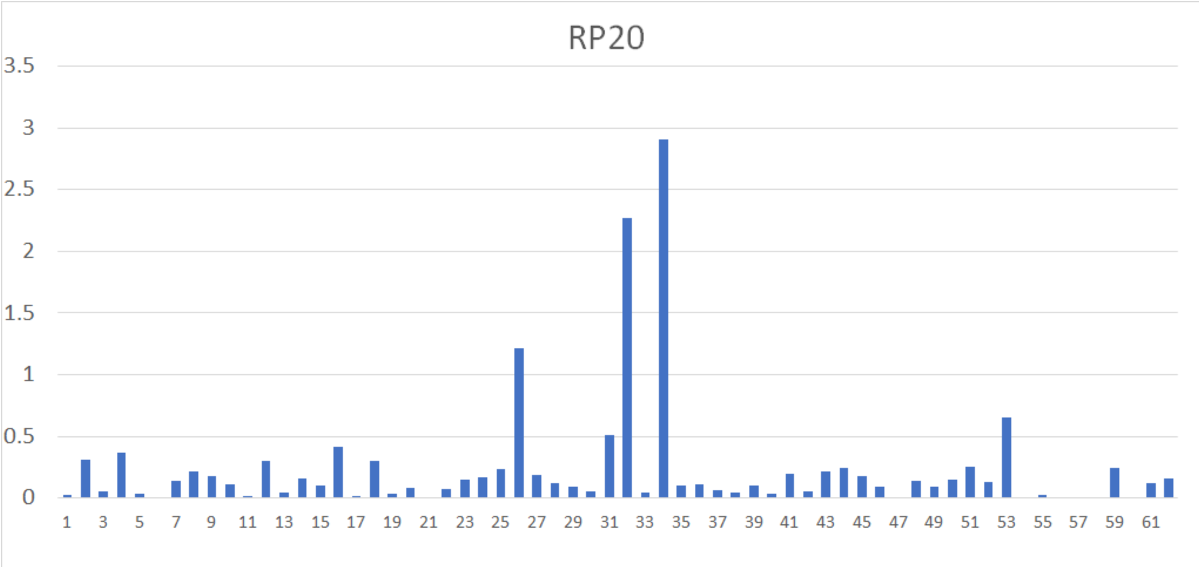

Figure 8: Effects with return period of 20 years (RP20):

RP20: The needed relative increases of the inputs of the respective sectors. The largest percentages are 2.90% in sector #35 (= H52-warehouses and support for transport) and 2.27 % in sector #32 (H50-water transportation).

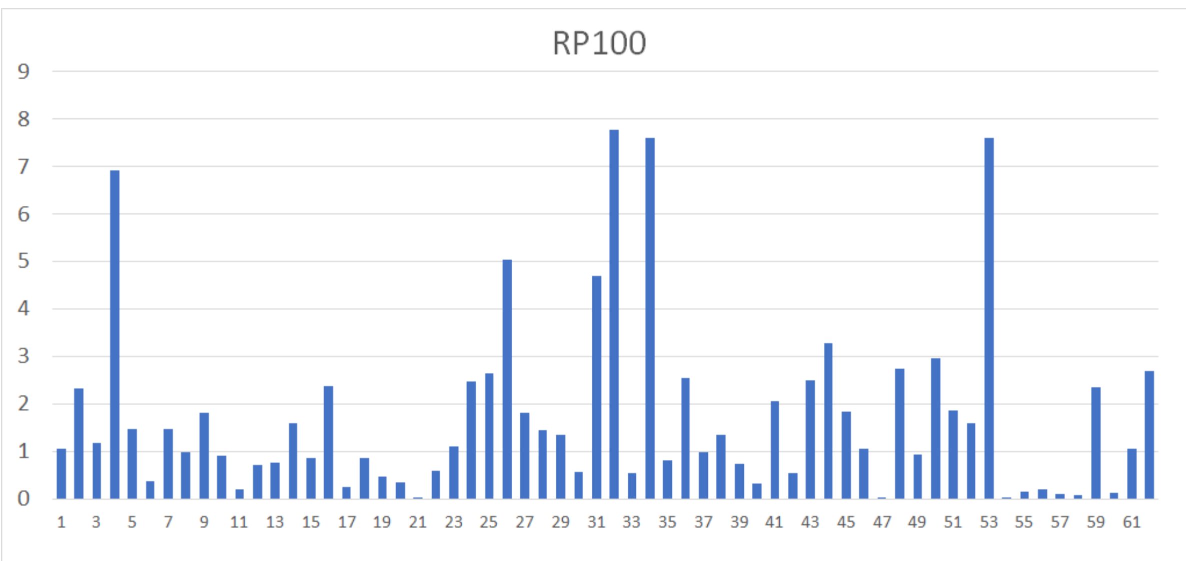

Figure 9: Effects with return period of 100 years (RP100):

RP100: Here the largest relative increases are: 7.77% (H50-water transportation), 7.61% (N80-82: security services, office administrative and support), 7.60% (H52: warehouses and support for transport), 6.90% (B: mining and quarrying)

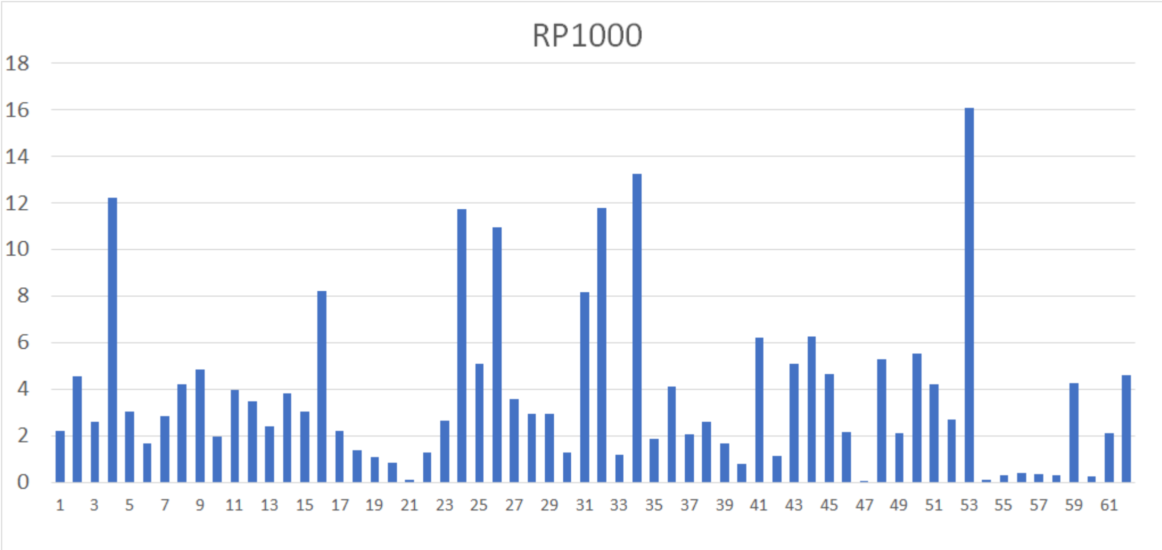

Figure 10: Effects with return period of 1000 years (RP1000):

RP1000: The largest relative increases are: 16.09% (N80-82: security services, office administrative and support) 13.27% (H52: warehouses and support for transport), 12.22% (B: mining and quarrying), 11.79% (H50: water transportation), 11.79% (D: electricity, gas and stream), 10.96% (E37-39: sewerage, waste collection, material recovery, remediation)

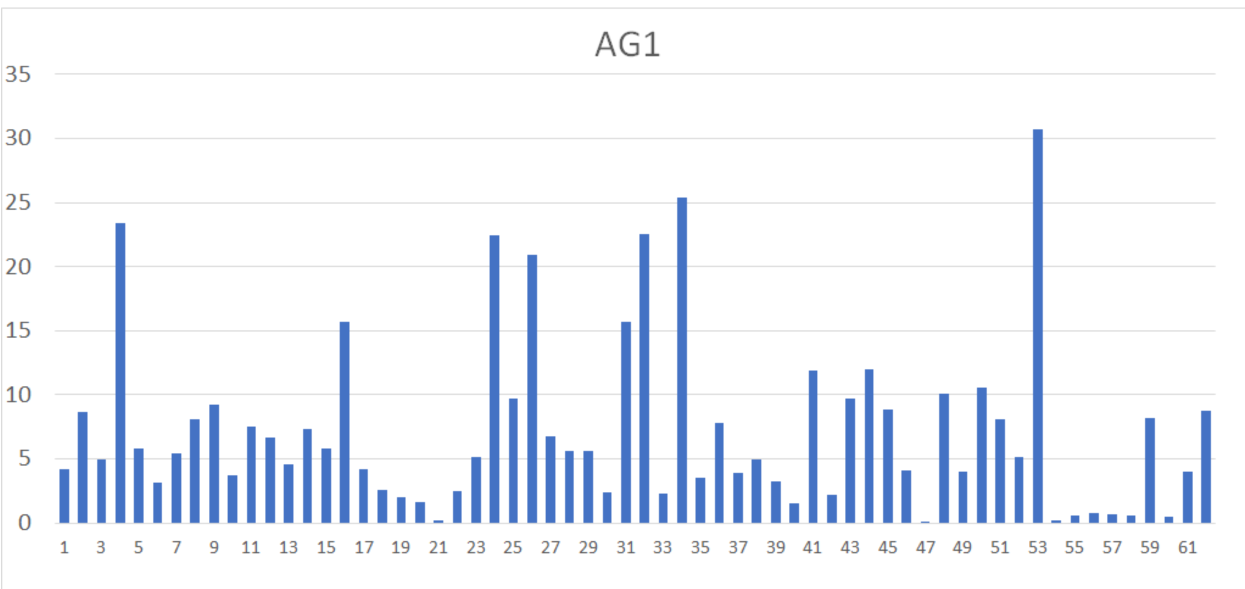

Figure 11: Effects under AG1

AG1: The largest relative increases are: 30.75% (N80-82: security services, office administrative and support) 25,36% (H52: warehouses and support for transport), 23.36% (B: mining and quarrying), 22.53% (H50: water transportation), 22.46% (D: electricity, gas and stream), 20.95% (E37-39: sewerage, waste collection, material recovery, remediation)

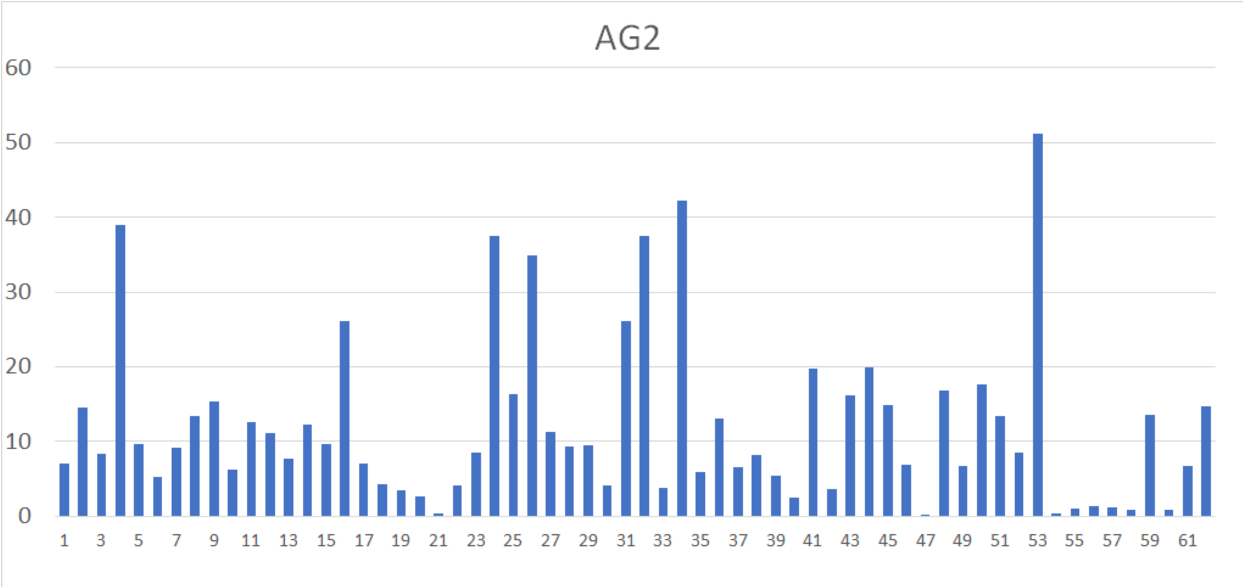

Figure 12: Effects under AG2

AG2: The largest relative increases are: 51.25% (N80-82: security services, office administrative and support) 42.28% (H52: warehouses and support for transport), 38.94% (B: mining and quarrying), 37.56% (H50: water transportation), 37.44% (D: electricity, gas and stream), 34.92% (E37-39: sewerage, waste collection, material recovery, remediation)

The AG 3 and AG4 scenario graphs are omitted as they are showing the same loss patterns as above with AG3: The largest relative increases are: 174.25% (N80-82: security services, office administrative and support) 143.75% (H52: warehouses and support for transport), 132.41% (B: mining and quarrying), 127.70% (H50: water transportation), 127.31% (D: electricity, gas and stream), 118.73% (E37-39: sewerage, waste collection, material recovery, remediation). For the AG4 the largest relative increases are: 348.5% (N80-82: security services, office administrative and support), 287.5% (H52: warehouses and support for transport), 264.83% (B: mining and quarrying), 255.41% (H50: water transportation), 254.63% (D: electricity, gas and stream), 237.46% (E37-39: sewerage, waste collection, material recovery, remediation).

It is especially interesting to see that the different exposure levels which are dependent on the flooded area (based on the Zoning system) have strong impacts on the distribution of increases in the sector rather than the magnitude. For example, the distribution of effects for figures for RP20, RP100 and RP 1000 (Figure 12) are quite different compared to AG1 with AG2.

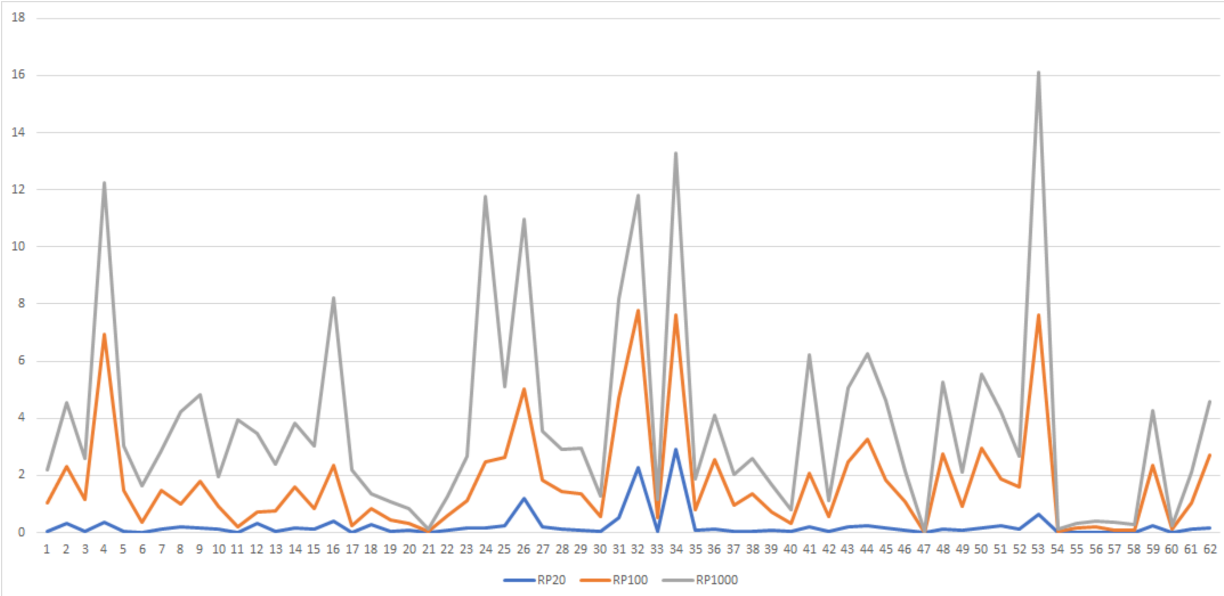

Figure 13: Comparison between RP20, RP100 and RP1000.

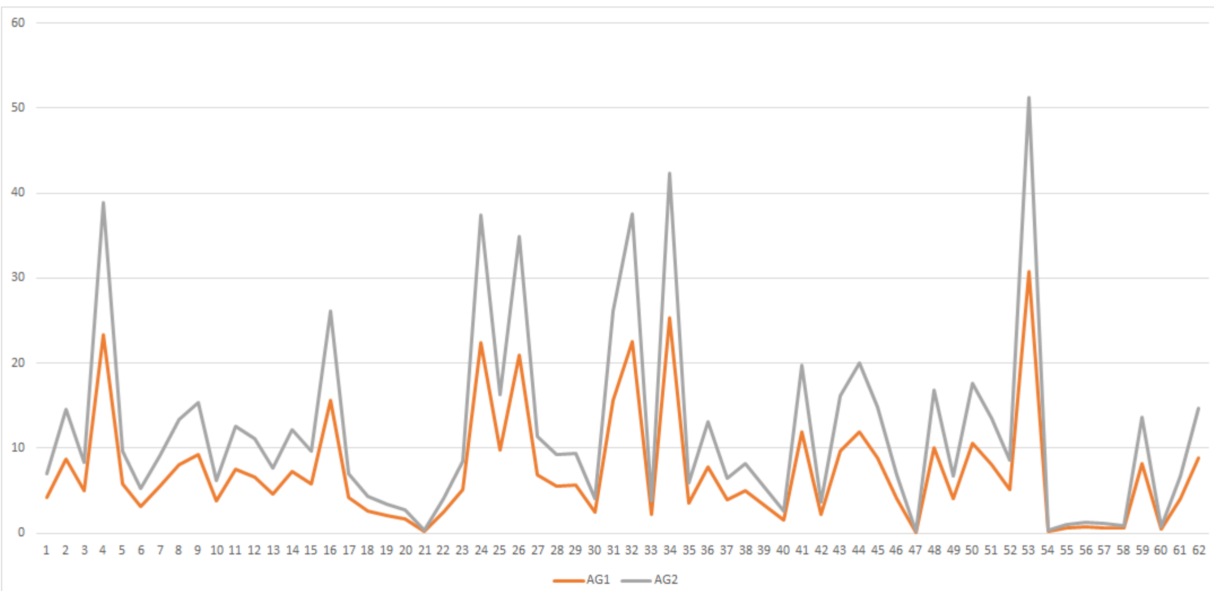

Figure 14: Comparison of increases in input for different sectors between AG1 and AG2.

In other words, for input output modelling the exposure changes for the different sectors due to different flood impacts may be of more importance for decision making than the absolute effects of the disasters.

2.2. Results from the computable general equilibrium model

Before explaining the results of the CGE model, we give an overview of the most important input data, i.e. the capital stock damages. Figure 15 gives relative sectoral capital stock damages (i.e. how many % of a sector are destroyed by a flood event) for the scenarios of a 1/20 (blue), 1/100 (red) and 1/1000-year (grey) event. In addition, the two extreme cases (Armageddon scenarios I and II) of a 3% and a 5% overall capital stock damage is included (empty and filled purple boxes, respectively). However, since Figure 15 only gives sectoral relative damages, it is not informative with respect to economy-wide effects, as it ignores the relative importance of the sector to the overall capital stock. We thus give an additional perspective in Figure 16, which shows how much of the economy-wide capital damage are attributed to which sector. Here the picture changes, with large and capital intensive sectors being most affected (e.g. REAL, NRGall, LTRA, SECO, STRA, LTRA, ACCO).

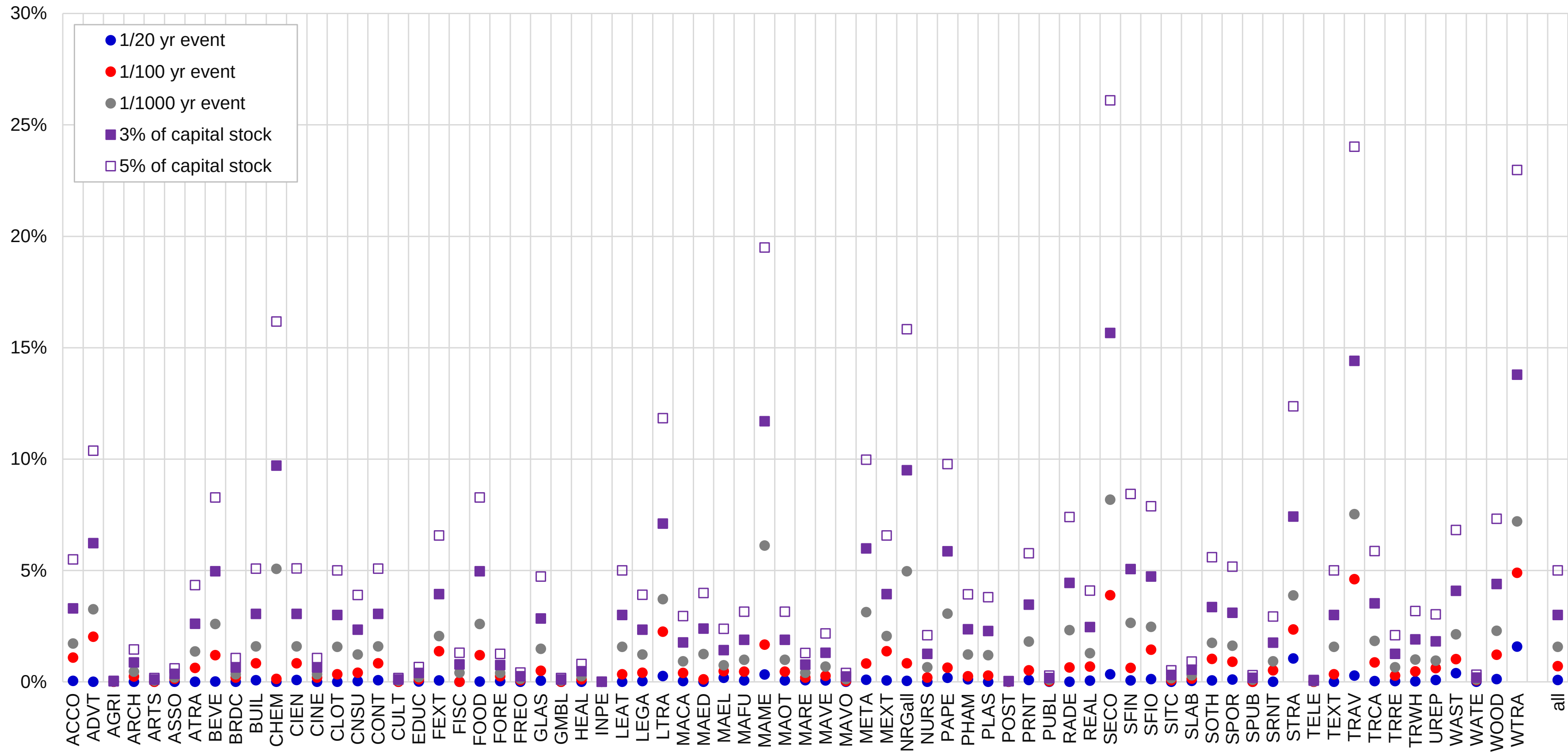

Figure 15: Relative damages to sector-specific capital stock by scenario for all sectors and for the economy as a whole ("all" to the very right)

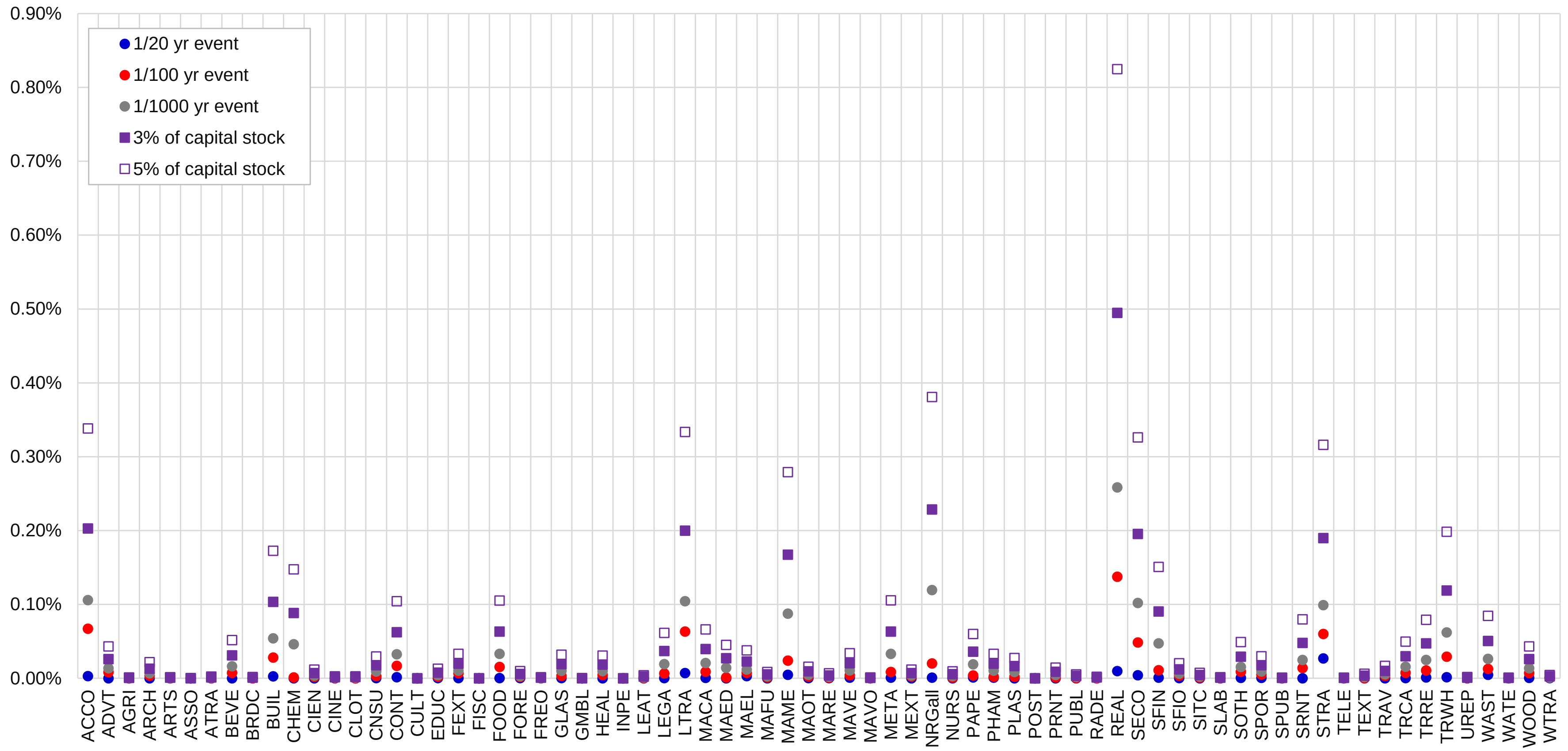

Figure 16: Sectoral damages relative to economy-wide capital stock by scenario.

Now, coming to the description of the results, we structure the 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 and interacting effect of these two channels.

We start analysing our results at the point of system intervention, i.e. the capital market in 2015 (t=1). From the damage channel we expect capital rents to be higher than in the baseline scenario, since the "remaining" capital of a sector (the fractions that are not destroyed) is getting scarce. However, as capital is sector specific, capital rents can also decrease due to excess supply pressures of capital in sectors which 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. As explained in section 1.4.6, reconstruction is modelled as additional forced investment, which partly crowds out generic investment as well as consumption (which mirrors necessary increased savings). From the reconstruction channel we thus expect that the capital stock of those sectors which are highly demanded in reconstruction activities 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 – capital rents are expected to decline as demand for consumption is crowded out. To summarize, the damage channel puts an upward pressure on capital rents due to scarcity, whereas the reconstruction channel puts a downward pressure to average capital rents due to lower demand.

Figure 17 shows the change in the average capital rent (left: for the scenarios 1/20, 1/100 and 1/1000 only; right: in addition the two high end impact events 3% and 5% capital stock destruction). Looking at 2015 we observe that for the high impact events average capital rents are higher than in the baseline, with the damage channel dominating. Only for the scenarios 1/20 and 1/100 the reconstruction channel dominates, which leads to slightly lower average capital rents in the year of the flood (note, that for some sectors capital rents are also increasing in these two scenarios, though. See Figure A 3 in the Appendix.)

In the post-event years (starting with 2016, t>1), we see that in all scenarios average capital rents are above baseline levels. 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 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 towards households with higher investment (savings) rates, and thus the capital stock grows stronger than in the baseline (see Figure A 4 in the Appendix).[3]

[3] Note that despite income is lower also for higher income households, the higher savings rate of higher income households overcompensates the income loss and leads to stronger economy-wide capital accumulation.

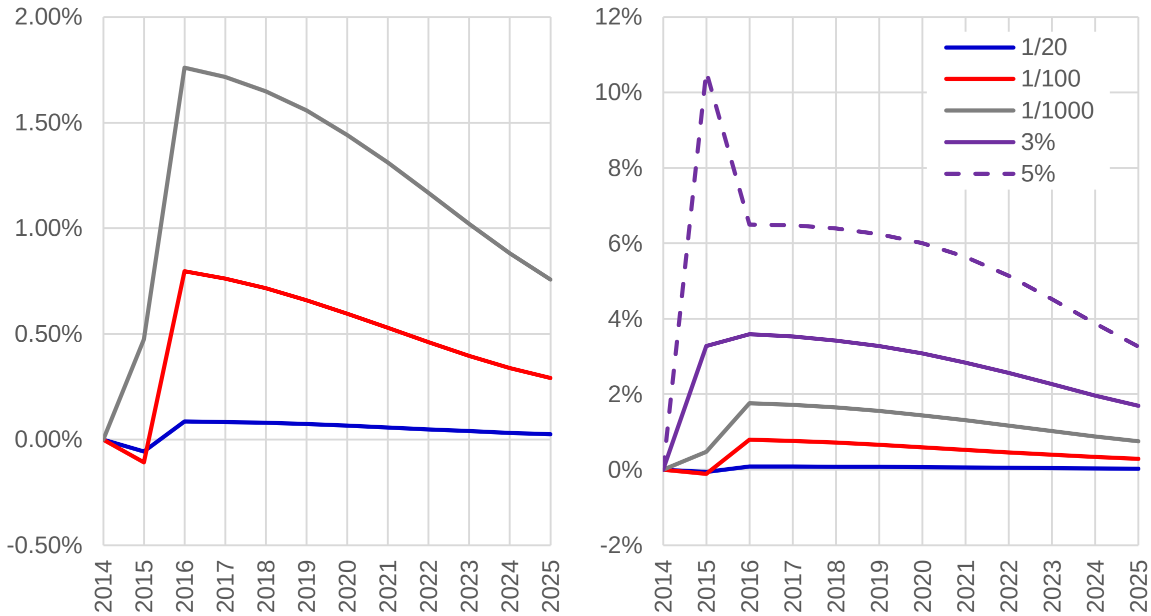

Figure 17: Change in average capital rent relative to baseline.

After having explained the effects on capital rents, we now explain how the production factor labour and the associated wage rate is affected. Note that in contrast to capital, labour is not sector specific and is thus perfectly mobile across sectors. Again, we explain the effect of wage rates via the damage and the reconstruction channel. After capital destruction labour is relatively more abundant and can not be used as productive as in the baseline any more (excess supply). Put differently, due to lower availability of capital, production is also lower and therefore labour demand is also reduced, which ultimately translates into lower wages.[4] Hence, the damage channels puts a downward pressure on wages. The reconstruction channel affects wages via the shift from relatively labour intensive consumption to more investment, which also leads to a downward pressure on wages.

[4] Since the standard assumption in CGE frameworks is that the labour market is cleared (i.e. no unemployment exists) and that labour supply is exogenous (bound to the working age population), it is the wage rate that brings the market to a new equilibrium.

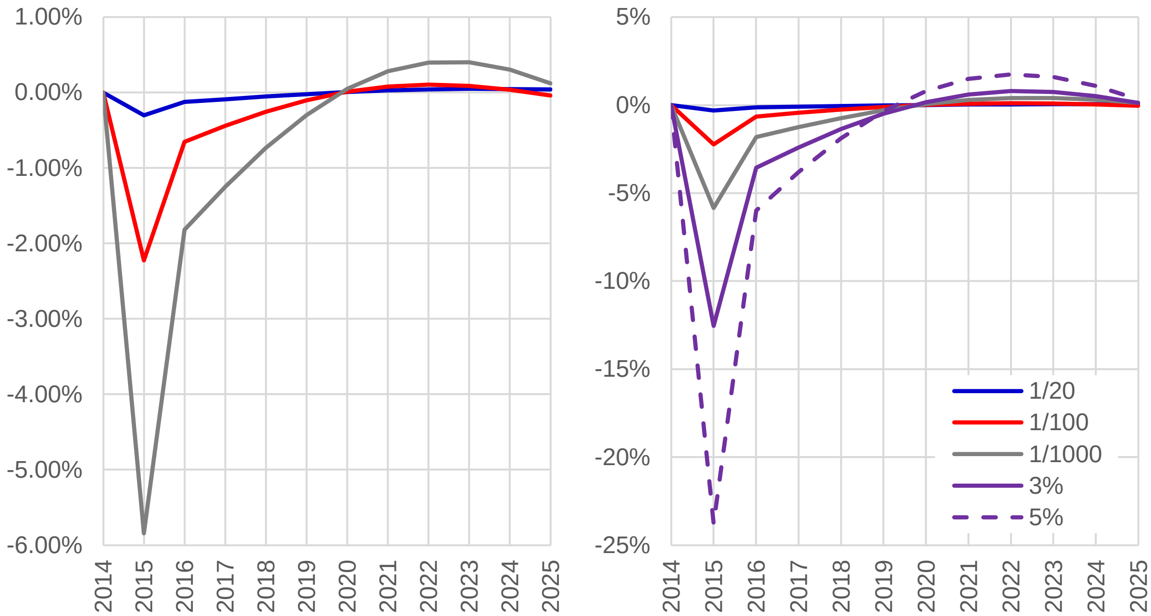

Figure 18: Change in wage rate relative to baseline.

Figure 18 shows the effects on the wage rate, relative to the baseline. Irrespective of the scenario, we observe a lower wage rate as in the baseline in the year of the flood event (2015, t=1), followed by a recovery in the subsequent years. When comparing the effects between capital rents and wage rate, we observe that the labour 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 onwards 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 (t=6) wages start to be above baseline levels. This can be explained by two effects. First, the capital scarcity effects is weakening over time, making labour more productive. Second, due to capital scarcity and higher capital rents there is a redistribution of income to higher income households (who own more of the capital stock than low income households). Since higher income households have higher expenditure shares for labour intensive consumption than low income households, demand for labour increases and so does the wage rate.

We now investigate economy-wide effects, by analysing the effects on GDP (Figure 19). 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 Figure 19. In fact, the effects on GDP closely follow the effect on the wage rate, as labour income is by far the largest source of income in the economy; followed by capital in tax income. Figure 20 shows the effects on GDP, decomposed by expenditure categories, illustratively for scenario 1/100. It becomes clear that the GDP effect is strongly driven by reconstruction activities, since only investments show an increase in the year of the flood (2015), whereas all other components (private and public consumption, export and imports) are below the baseline.

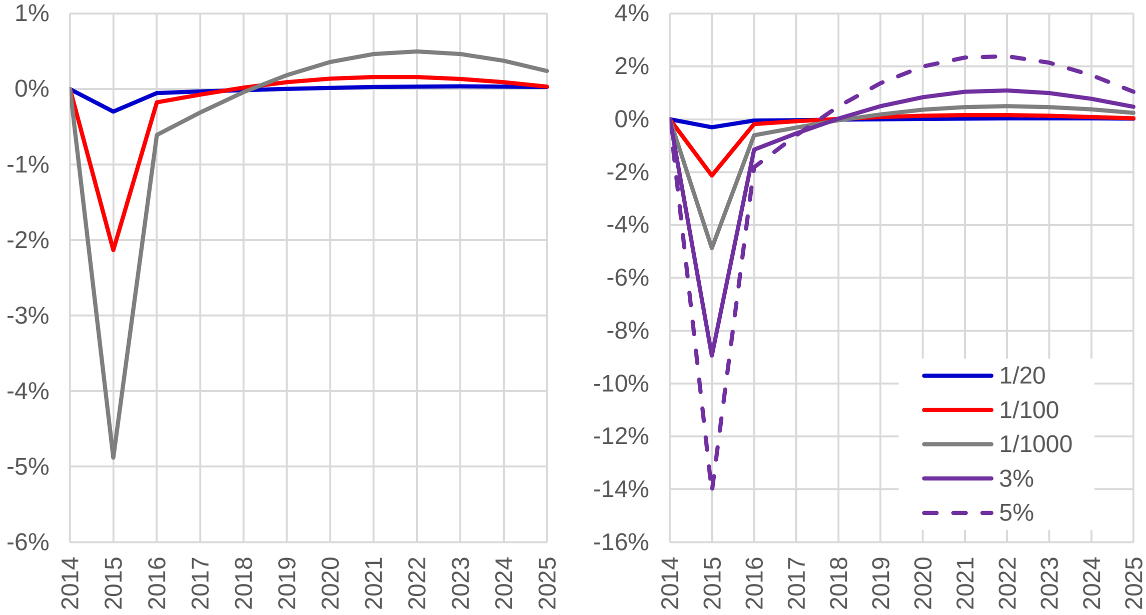

Figure 19: Changes in GDP relative to the baseline.

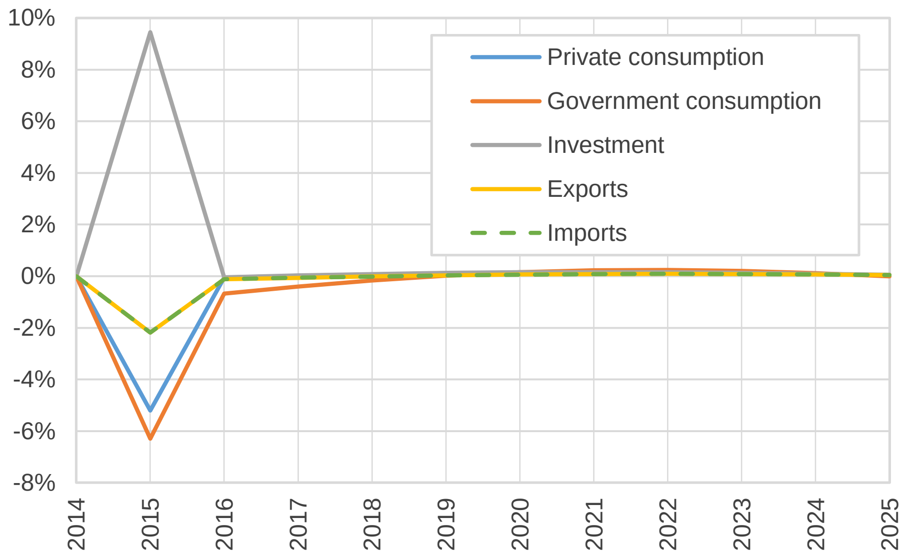

Figure 20: Decomposition of GDP by expenditure components. Changes relative to baseline for scenario 1/100.

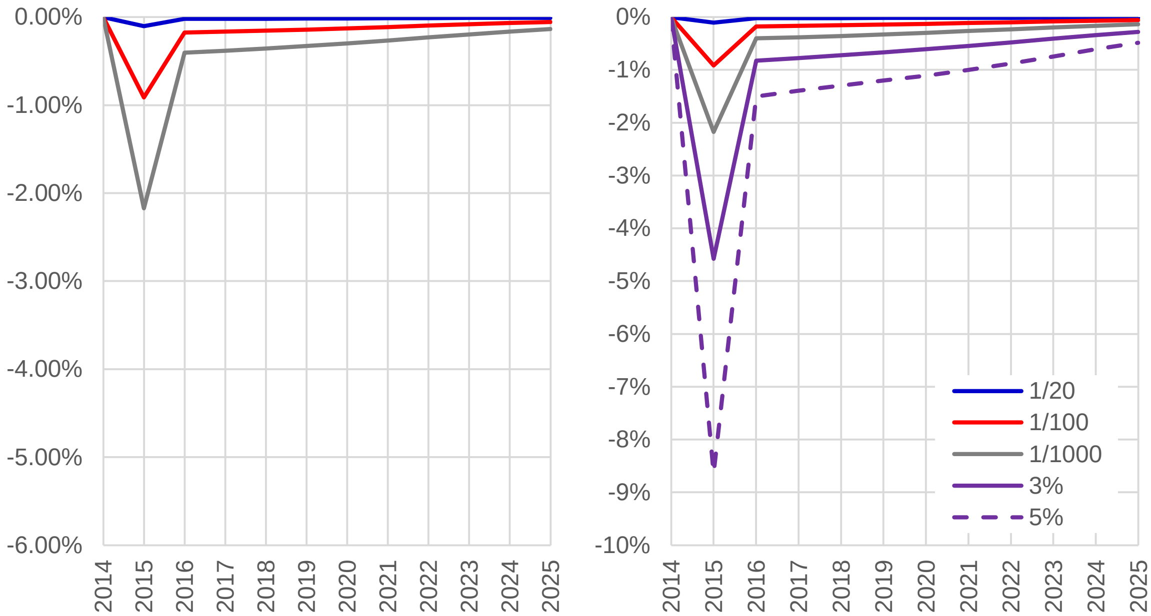

Figure 21: Changes in GDP relative to the baseline (constant prices of base year 2014).

Figure 21 gives change in GDP at constant (2014) prices, thus not including relative price changes from indirect effects (GDP is calculated from the expenditure side as the sum of consumption, investment and net exports). Compared to Figure 19 the positive effects from higher wage rates disappear, meaning that when measuring GDP in terms of quantity effects only, it does not reach levels above the baseline throughout the whole time horizon.

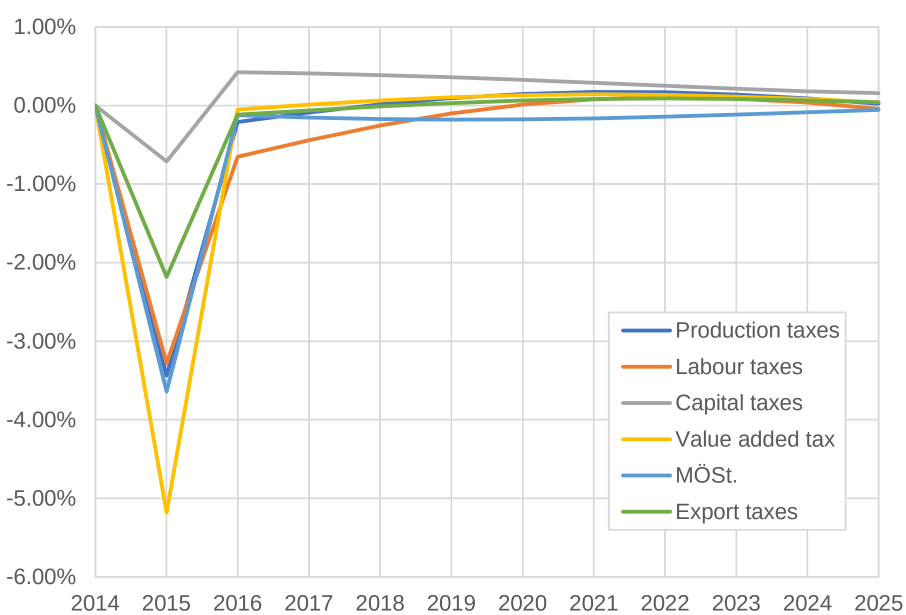

Figure 22: Change in tax income by income source. Changes relative to baseline for scenario 1/100.

As visible Figure 20, public consumption is lower than in the baseline due to the flood event. This is because tax income is lower, which is shown in more detail in Figure 22. We see that in the year of the flood event

(2015) consumption tax income (VAT) is reduced strongest, followed by production and labour tax income. The tax loss effects weaken over time, however in the first years after the flood tax income is still below the baseline. Total tax income reaches the baseline level only five year after the flood.

We now take a closer look at different households, their consumption possibilities and welfare implications. As shown in Figure 20 the value of consumption falls below the baseline level. However, as we are interested in consumption *possibilities*, rather than the monetary value of consumption, we correct for relative price changes and only measure the consumption quantity effect. Put differently, we measure the consumption possibilities after prices and incomes have changed. This is what we call "welfare" (in economic terms Hicks'ian Equivalent Variation).

Figure 23 shows how consumption possibilities change for households, differentiated by income quartiles and location of residence; again illustratively for the 1/100 scenario. In addition, we show the quantity effect of government 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, t=1) the negative effects are strongest for high income households (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 lose a higher proportion of their income due to the damage to the capital stocks. Also, lower income households receive lower fractions of their income via factor provision (labour or capital supply), as their income structure is characterized by higher shares of public transfers. When comparing the private consumption effects to the one of 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 possibilities.[5]

[5] This is based on the assumption, that one euro of public service provision has the same welfare effect for all household types.

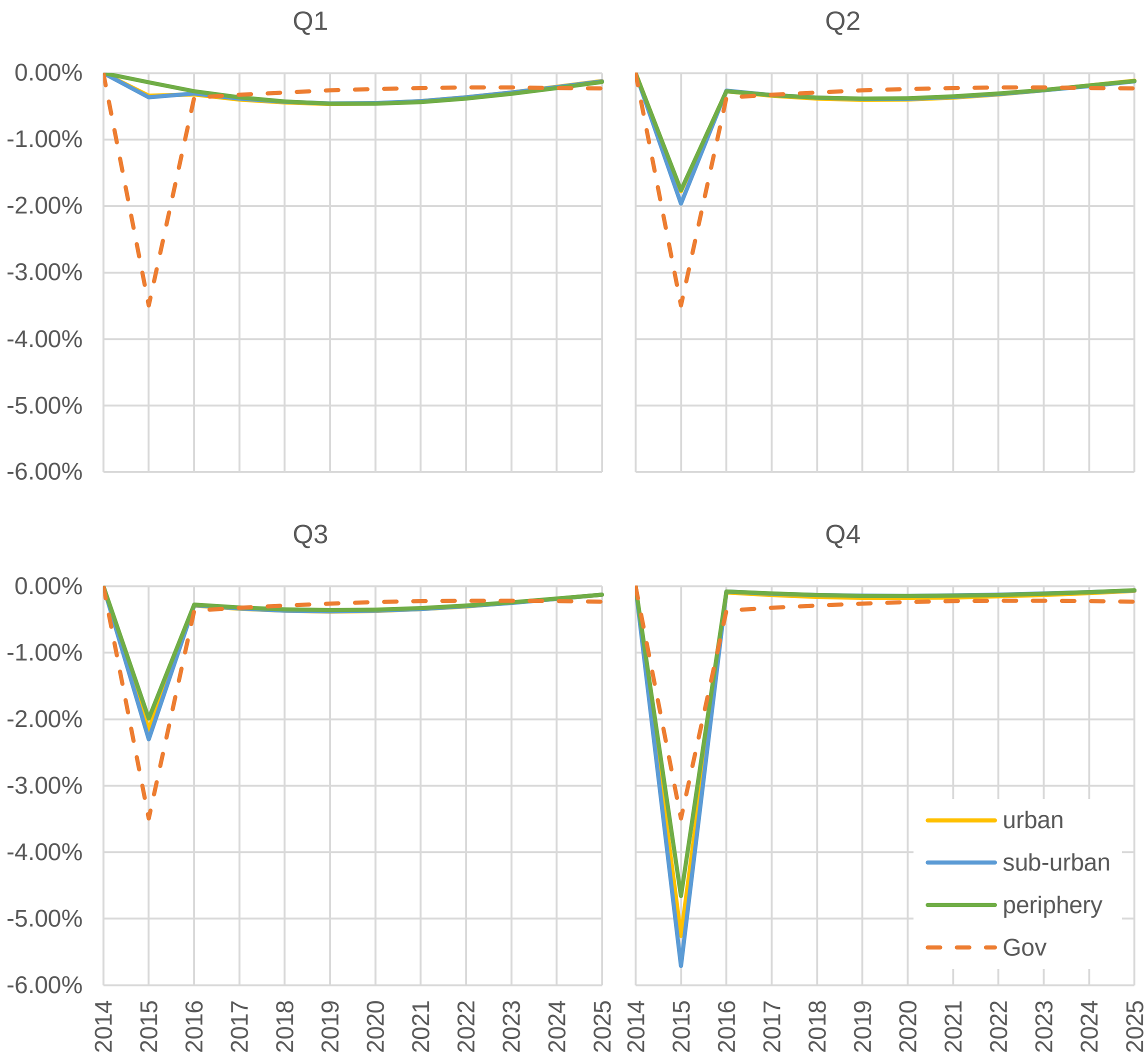

Figure 23: Consumption quantity effects by income quartile (Q1=first, Q2=second, Q3=third, Q4=fourth) and location of residence (urban, sub-urban, peripheral) as well as effects on quantities of public service provision (Gov) relative to baseline for scenario 1/100.

When looking at the periods after the flood event (Figure 24), we see that consumption possibilities remain below the baseline level for all household types and also 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 which are affected strongest and that the negative effects are getting less severe with rising income. This effect can be explained by two forces: 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 labour intensive consumption goods. Since capital costs (rents) increase and labour costs (wages) decrease, this means that higher income households have a comparative advantage vis-à-vis lower income households. Second, also the income structure varies across household types, with higher capital income shares for high income households and higher labour income shares for low income households. Hence, also due to factor price changes, low income households are worse off.

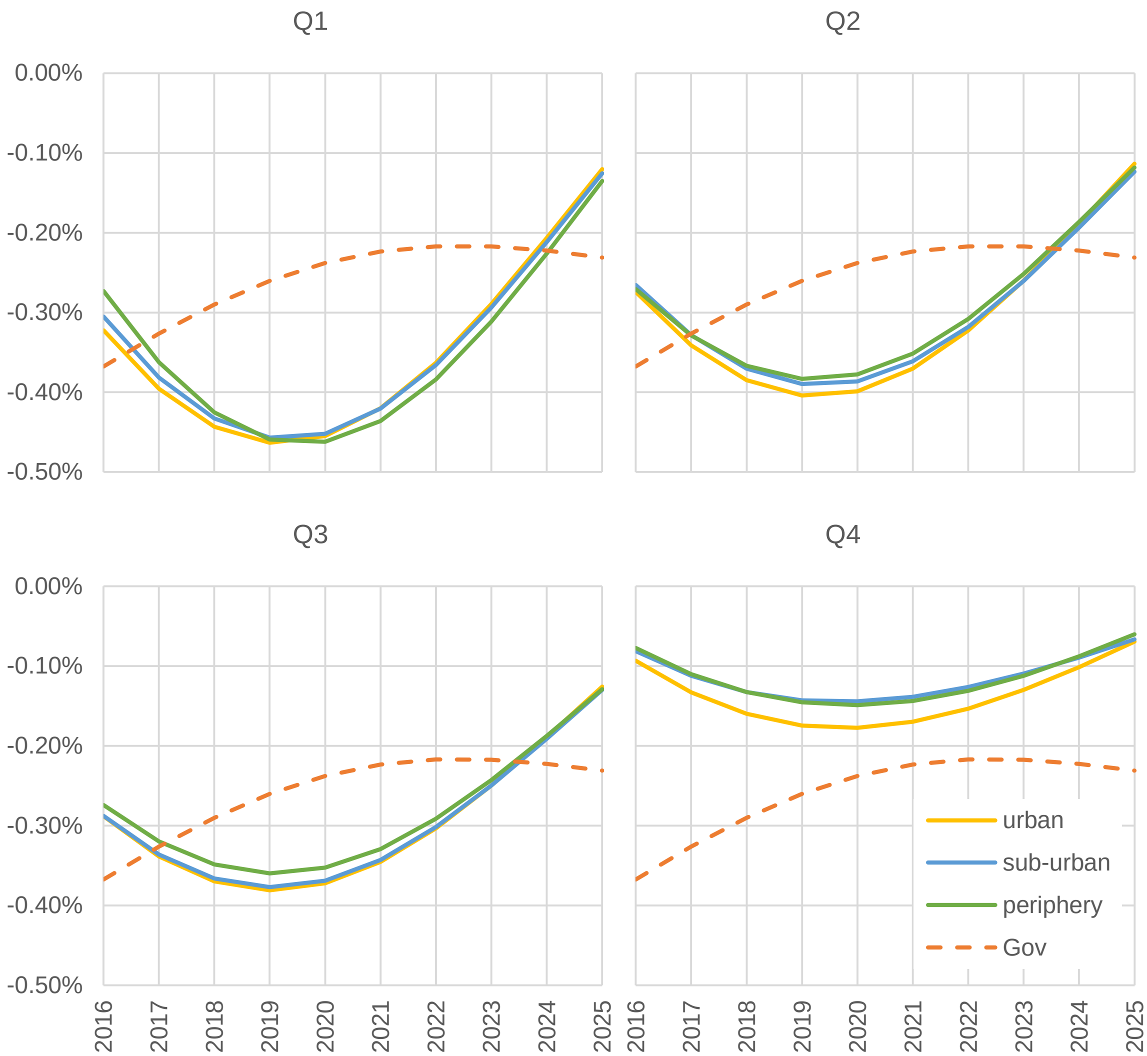

Figure 24: Consumption quantity effects by income quartile (Q1=first, Q2=second, Q3=third, Q4=fourth) and location of residence (urban, sub-urban, peripheral) as well as effects on quantities of public service provision (Gov) relative to baseline for scenario 1/100 and only for years beyond the flood event.

After having analysed potential indirect risks of major flood events in terms of distributional effects, we turn to the sectoral perspective; i.e. how different economic production sectors are affected. In general, sectors are affected by the direct damage to its capital stock, 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.

Figure 25 shows how sectoral output changes in 2015 with respect to the baseline for the 1/100 scenario. We see that most sectors operate at a lower activity, i.e. produce less. Those sectors which are highly demanded for reconstruction have a higher output though (up to +20% for the buildings sector BUIL).

What would be more interesting than plain output changes for measuring indirect risk is how much a sector loses in terms of value added and how this loss of value added relates to the direct capital loss. Put differently, we want to measure, 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 indirect risk as $IR = GVA_i / KD_i$, where GVA_i is gross value added of sector i and KD_i is the capital damage to sector i's capital stock. A value if IR>1 means that the lost GVA is larger than the direct capital damage ("high" indirect risk). If IR=1 it means that lost GVA and direct damage are the same. A value of 0<IR<1 means that the sectoral GVA loss is smaller than the direct damage ("low" indirect risk), but there is still a loss. A IR<0 value would mean that gross value added can be increased, even though there is a direct damage to the sector (benefit of flood event).

Figure 26 gives the calculated IR for sectors with IR>0, Figure 27 gives IR for sectors with IR<0 (i.e. 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, indicated very high IR's for those sectors (note the log scale in Figure 26). For some sectors the lost GVA is 100-1.000 times higher than the direct damage, due to economy-wide feedback effects. Only about 1/3 of the sectors show a low indirect risk with GVA losses being smaller than direct capital stock damages. Looking at the negative IR-side, we see again those sectors which contribute to reconstruction (construction, buildings, manufacturing of cars, civil engineering etc.).

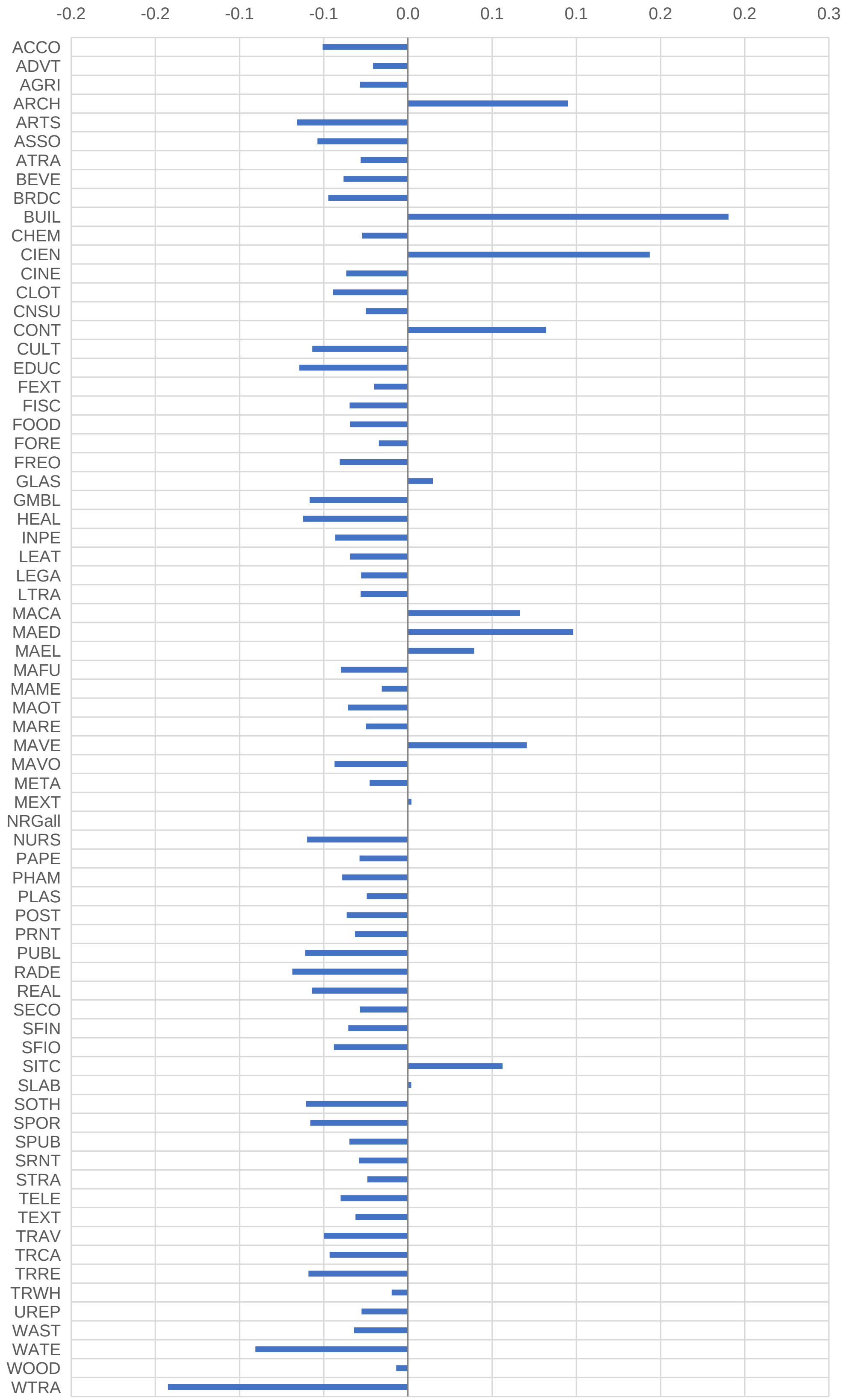

Figure 25: Sectoral change in output in 2015 for scenario 1/100.

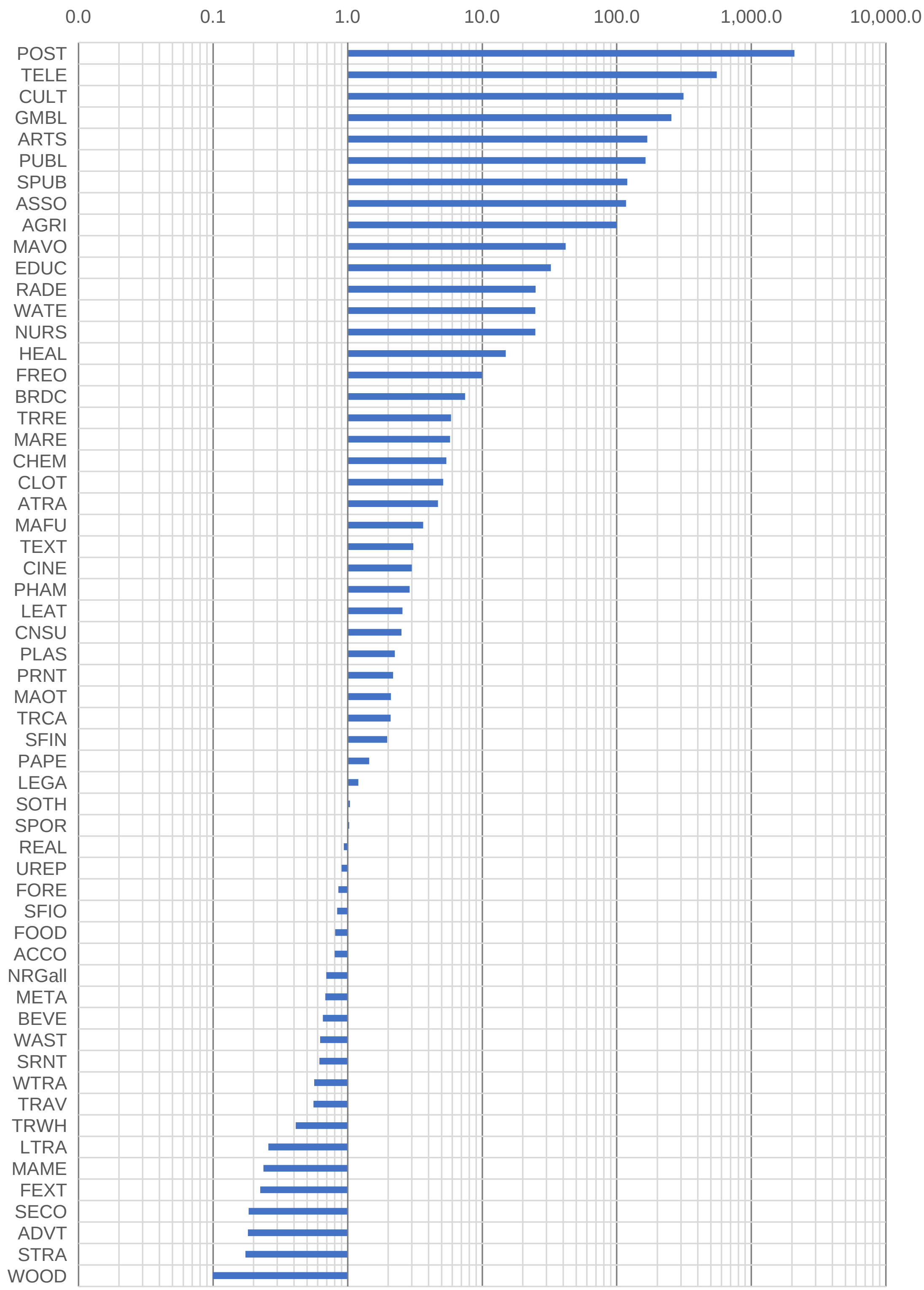

Figure 26: Indirect risk by sector measured as the ratio of lost gross value added (GVA) relative to direct capital stock damage in 2015 for scenario 1/100. Values above one indicate higher lost GVA than direct damage to sectoral capital stock (e.g. a value of 2 means that lost GVA is twice as large as the direct damage to the capital stock), values below one indicate lost GVA as a fraction of direct capital stock damage (e.g. 0.1 means that lost GVA is 10% of capital stock damage).

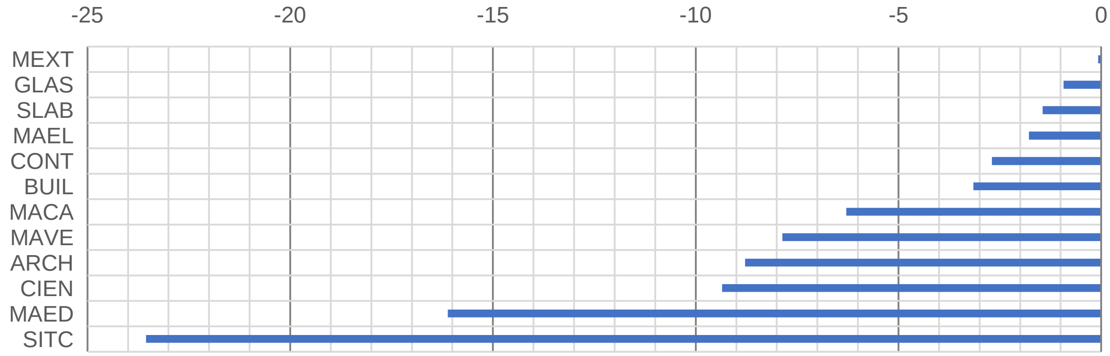

Figure 27: Indirect benefits sector measured as the ratio of lost gross value added to direct capital damage in 2015 for scenario 1/100. Negative values indicate that gross value added can be increased despite positive capital stock damages (e.g. -20 means that GVA is increase by 20 times the damage to the capital stock).

2.3. Results from the agent-based model

Figure 28 shows the indirect economic effects resulting from a 100-year (red line) and a 1000-year (black line) flood event that destroys dwellings and productive capital. The total direct losses (damages) amount to about 0.7% (100-year event) and 1.57% (1000-year event) of Austrian capital stock, respectively. Figure 28 depicts 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[6] in percentage points (pp).[7] The qualitative behaviour of the 1/100 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. In the long term, primarily due to a multiplier accelerator mechanism (Samuelson, 1939), the economy seems to remain on a higher GDP level than before, while the GDP growth rate returns to its previous value. These effects are most pronounced with an almost 2pp GDP growth rate increase (1000-year event) relative to the baseline scenario in the first year after the flood (2015). In the medium term, the effects decline to a slightly negative impact, while the growth effects in the long term seem to be largely neutral. This behaviour i.e., 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 28 (lower right panel) also demonstrates that—as to be expected according to Okun's law—the change in the unemployment rate is inversely correlated to economic growth: for the 1000-year event, a decline of slightly more than 1pp within two years after the flood consolidates in a 1pp decrease of the

[6] 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.
[7] A percentage point (pp) is the unit for the arithmetic difference of two percentages. For example, moving up from 10% to 12% is a 2pp increase, but it is a 20% increase in what is being measured.

unemployment rate in the long term, in line with the effect on the GDP level. Figure 28 (lower left panel) depicts the government debt-to-GDP ratio and shows that the dynamics of the growth and unemployment rates, as well as the transfer we assume to be provided by the government to fully compensate households for their losses of dwellings as catastrophe relief, all lead to an initial fall in this ratio of about 2pp for the 1/100 and 1/1000-year events. In the long term after the flood (2016-2019), the government debt-to-GDP ratio steadily declines to an overall decrease of more than 3pp (1000-year event) due to the long-term increases of GDP levels and the corresponding decrease of the unemployment rate.

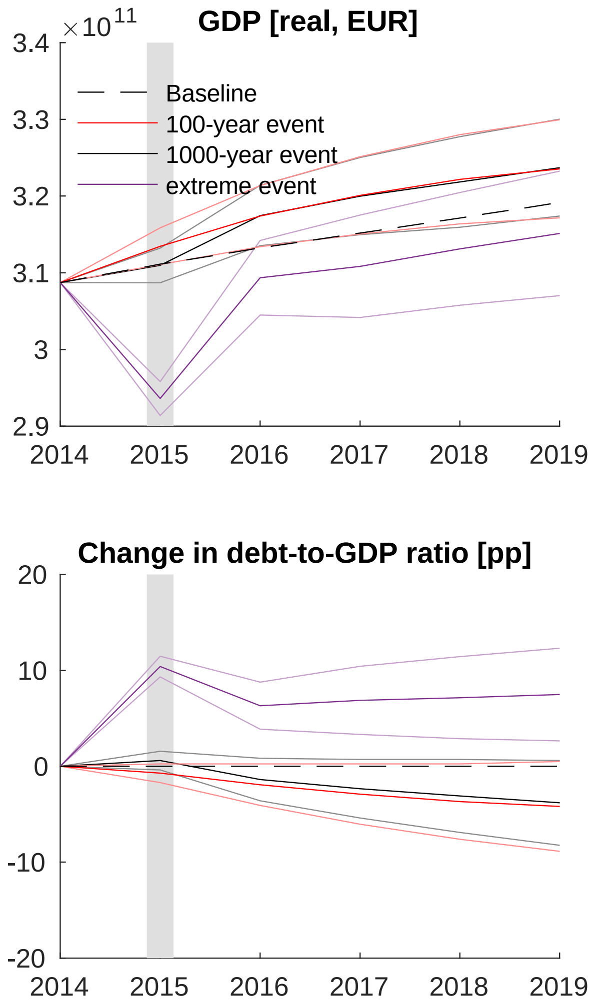

Figure 28: Indirect economic gains and losses of a 100-year (red), 1000-year (black), and extreme (purple) flood event. Time labels on the x-axis indicate the end of each year, and the grey vertical bar marks the first year after the flood. The panels show the effects as changes relative to the baseline 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.

An extreme-disaster scenario is also shown in Figure 28 (purple lines). The total direct losses correspond to approximately 5% of the capital stock in Austria. The indirect economic effects after this shock are qualitatively different from the moderate-disaster scenarios. The initial overall effect on GDP growth is pronouncedly negative, with a reduction of GDP growth by about 6pp, see Figure 28 (upper right panel). Due to reconstruction, growth picks up fast in the year after the disaster and surpasses GDP growth of the baseline scenario by the second year after the flood, culminating in a temporary economic boost of about

4pp of additional GDP growth in 2016. However, the multiplier-accelerator mechanism (Samuelson, 1939), as well as production, capacity, and credit constraints (see Poledna et al. (2020)) drag growth downwards after this point with almost neutral growth effects in the long run. The change in the GDP level (upper left panel) remains also negative in the long term, due to the large initial damages and the cyclical dynamics induced by the disaster. The unemployment rate reacts strongly to the extreme disaster, with an initial increase of more than 4pp right after the disaster and is followed by an increase of about 2pp in the long run (see Figure 28, lower right panel). The long-run behaviour of the unemployment rate again corresponds to the changes in the level of GDP. Immediately after the disaster, a large initial government transfer to households to compensate for their losses of housing stock,[8] as well as substantial decreases in government revenues and GDP, lead to a more than 10pp rise of the government debt-to-GDP ratio (see Figure 28, lower left panel). This ratio does not return to its initial level despite the positive economic effects of reconstruction, leaving government finances deteriorated in the long term.

[8] We assume—in line with past experiences of political processes regarding catastrophe relief by the Austrian government—this transfer to be limited to about a third of the total losses in dwelling stock.

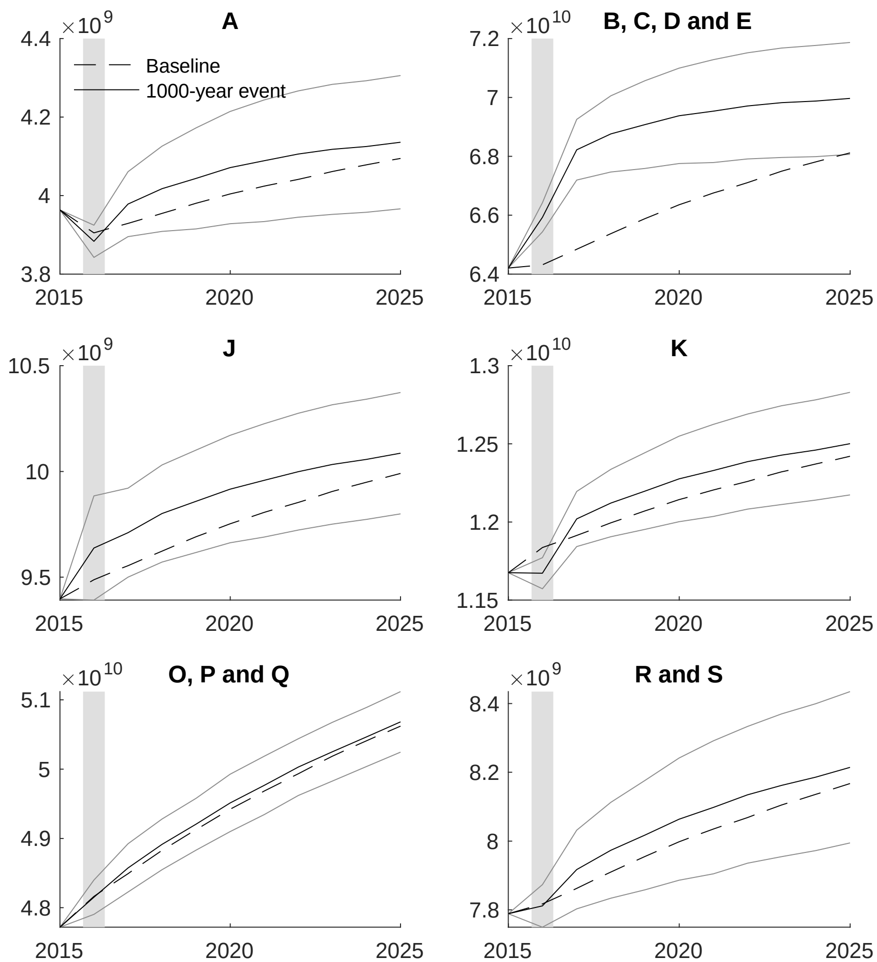

Figure 29: Effects of the 1000-year event disaggregated for ten economic activities (sectors). Sectors shown: agriculture (A), manufacturing, mining and quarrying, other industry (sectors B, C, D and E), construction (F), wholesale and retail trade, transportation and storage, accommodation and food services (G, H, and I), information and communication (J), financial and insurance services (K), real estate activities (L), professional, scientific, technical administrative and support service activities (M,N), Public administration and defence, compulsory social security, education, human health and social work activities (O, P, Q).

While moderate flood events can have positive aggregate effects in the medium term, impacts are expected to differ significantly across economic sectors. Figure 29 confirms this conjecture. It shows the effects of the 1000-year event disaggregated for ten economic activities according to national accounting conventions. The real estate sector (sector L) suffers substantially from the destruction of residential capital stock as sectoral output is reduced substantially at the beginning. However, due to reconstruction activities, sectoral output soon surpasses its initial level. The construction sector (sector F) immediately profits from the reconstruction of dwellings and productive capital in the first year after the flood (2015). After the fast ramp-up of reconstruction during the first years after the flood, peaking in an increase in the second year after the flood (2016), this effect gradually wears off in the following years but remains at a slightly elevated level in the long run. The restoration of productive capital takes more time. The largest cumulative increase for the manufacturing industry (B, C, D, and E) is reached in year two after the flood (2016) since this sector supplies a major part of the material input for the re-instalments of losses in productive capital. After this point, the output for these sectors remains at a stable path above its initial level for the long run. The effects on all other sectors are less pronounced. Sectors O, P, Q, R, and S are initially slightly impacted due to building structures harmed by the disaster, but again output rises above its initial level, if only slightly. For all other sectors (A, J, K, M, and N) effects also remain slightly positive, sometimes after an initial overshoot.

3. Model comparison

To better understand the differences between different model results we first briefly discuss the theoretical differences between the three models at hand, followed by a direct comparison of results for the indicators GDP, capital stock development as well as value added.

3.1. Theoretical differences between model classes

A major source of (economic) model uncertainty is 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 the neoclassical 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, must 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 to GDP, as reconstruction crowds out otherwise 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, post-Keynesian models or ABMs assume that the economy can grow by demand stimulus; e.g. by reconstruction. This assumption implies that (physical) production capacities are idle and can be activated by increased demand (e.g. financed by public debt). This assumption mirrors the economic state of an economy in recession, where capital and labour are not fully used and can be activated by demand stimulus.

Another difference in economic macroeconomic modelling is the assumption of behaviour. On a spectrum where statistical (or econometric) models lie at one end, ABMs together with CGE models lie at the other. Opposed to statistical models, both ABMs and CGE models are based on micro-foundations, however of different forms. With respect to behaviour, the key difference between these two types of models is as follows: CGE models assume that agents optimize their behaviour, assuming perfect information about market prices (in fully dynamic model even about the future state of the economy), while ABMs assume that agents use simple heuristics to consume, produce, invest, work, hire, and conduct all other economic activities. ABMs thus depict boundedly rational expectations with agents using simple forecasting heuristics to navigate their complex economic environment—the exact structural rules and determinants of which are not known to them, i.e., they are faced with "Knightian" (Knight, 1921) or "fundamental" (Keynes, 1936) uncertainty. Post-Keynesian IO models typically also assumed simple and econometrically estimated rules on how agents behave.

Another difference between IO, CGE and ABMs is how these types of models are solved. While ABMs are solved numerically at the agent level, behavioural rule by behavioural rule, CGE models are solved numerically at the aggregate level. IO models are solved analytically as they are typically linear models.

When comparing the three model classes at hand, all of them have their strengths and weaknesses and one could think of the best purpose of their application. When doing so, it becomes evident that the different models are suited for analyses of different time horizons. Standard IO models are completely static, i.e. they mimic the very short-term behaviour of economies where technological change or changes in production and demand structures are not possible (due to the fixed input coefficients). Hence, IO models can be used to detect bottlenecks or very short-term effects of demand stimulus (assuming that there are none of them). The ABM as used here is best suited to describe short to medium-term effects, i.e. effects over 1-5 years (divided into annual quarters) as it is calibrated to rather short-term behaviour and expectations of agents (behavioural heuristics). Finally, the CGE model assumes long-term macroeconomic balances and equilibria and is therefore best used to study the long-term effects of a system intervention. The direct comparison of model results is thus of limited meaningfulness in terms of plain numbers, nevertheless we do so to reveal modelling 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).

3.2. Comparison of model results

The comparison of model results is carried out for the ABM and the CGE model and the following indicators: GDP and fixed assets in total (i.e. capital stocks), sectoral gross value added (GVA) and sectoral fixed assets to represent sectoral impacts from flood shocks. While the former two represent overall economic performance in the year of the flood event and the following years, the latter two represent sectoral impacts from flood shocks, which greatly vary as flood damages are sector-specific.

Figure 30 depicts changes in GDP (left) and in fixed assets (right) for three scenarios: the 100yr flood event, the 1000yr flood event and the theoretical scenario of a destruction of 3% of total fixed assets. The solid lines represent the results of the CGE model and the dashed lines the results of the ABM. Concerning the consequences for GDP, the effects in the ABM for the 100 and 1000yr flood event are only negative in the first quarter of the shock year, but turn positive thereafter. In contrast, while GDP losses in the year of the shock are smaller in the CGE model compared to the ABM (-1% vs -2% with the 100yr flood event and -3% vs -4% with the 1000yr flood event), they are always negative within the investigated time horizon. This is because the CGE model treats the flood event as a productivity shock and as it is assumed that reconstruction is financed by reductions in consumption but also generic investments (savings), the capital accumulation effect is weaker as

in the baseline scenario. This is not the case in the ABM, where production capacities are assumed to be idle and reconstruction thus stimulates growth.
The more pronounced reaction of the GDP in the first time step of the ABM can be explained by the shorter time steps. As introduced earlier, the CGE model solves on annual basis, thereby smoothening the effect, which are displayed in the ABM, that solves quarterly for each year.
While the differences across the different flood scenarios are only a matter of scaling in the CGE model, the ABM depicts structural differences. Thus, the largest damage scenario among these three scenarios also leads to continuous negative GDP effects in the ABM with a very strong initial effect of roughly -10% in the first quarter of the shock year and a quick recovery before GDP losses start rising again.
Concerning the consequences for fixed assets, the picture is reverse in the sense that the effects identified in the CGE model exceed those in the ABM. While there is hardly any effect in the smallest damage scenario in the ABM, fixed assets are lower by -0.5% and -3% in the 1000yr flood event and the 3% destruction scenario, respectively, in the initial time step. However, also these negative impacts quickly recover after the first year and even turn positive, as agents react to rebuild destroyed assets. The losses in the CGE model are both more pronounced in the first year and persist over the investigated time horizon due to lower capital stock accumulation.

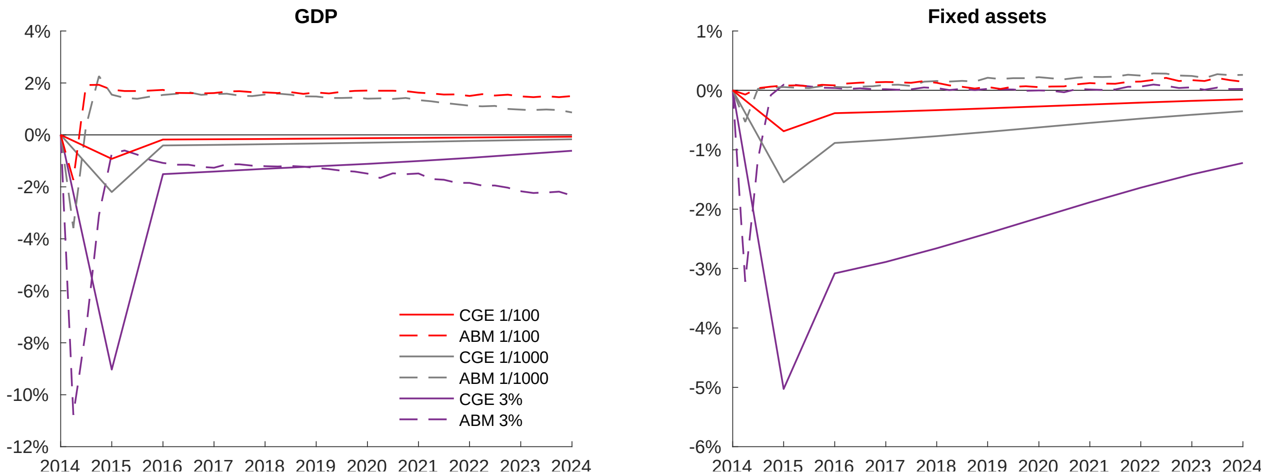

Figure 30: Comparison of CGE model and ABM. Changes in GDP (left) and fixed assets (right) relative to the baseline (constant prices).

Figure 31 presents the differences in results for individual sectors' or sectoral clusters' gross value added (GVA). The solid line again refers to the results identified in the CGE model and the dashed line in the ABM. For illustration purposes, we depict only the 1000yr flood event. For the majority of sectors, the CGE model depicts a substantially more pronounced effect than the ABM. However, results differ with respect to the sectors. For three groups of sectors (O, P and Q; R and S; and L), there are virtually no effects in the ABM, but losses up to -15% of GVA in the CGE model in the initial time step. These sector groups include the publicly provided as well as finally demanded goods and services, and real estate activities. In contrast, three sector groups (A; G, H and I; and K) show an initial negative effect in the ABM, but then return to 0 or even stay slightly above implying an increasing GVA. In the CGE model, these sectors, including agriculture and forestry, wholesale and retail trade, transport, accommodation and food service activities, as well as financial and insurance activities, loose GVA of up to -10% and stay below baseline levels throughout the investigated time horizon.
A further group of sectors (B, C, D and E; and F) provide necessary input for reconstruction activities after the flood event, such as the construction and manufacturing sectors. These sectors react in both models with an

increase of GVA immediately after the time period of the shock, which is the first year in the CGE model, but only the second quarter of the year in the ABM. Thereafter, both models show that GVA returns towards baseline levels with this behaviour being slower in the ABM. The sectors M and N, including professional, scientific and technical activities, as well as administrative and support service activities, show a similar pattern in the ABM as it complements reconstruction activities but does not show strong effects in the CGE model.

The GVA of the sector J, information and communication, strongly increases in the ABM shortly after the flood event, where it has a short peak and then decreases again but stays substantially above baseline levels at about +2%. Results of the CGE model show a similar pattern, but with only moderate increases at first followed by a decrease below baseline levels and a tendency to return to baseline levels towards the end of the investigated time horizon.

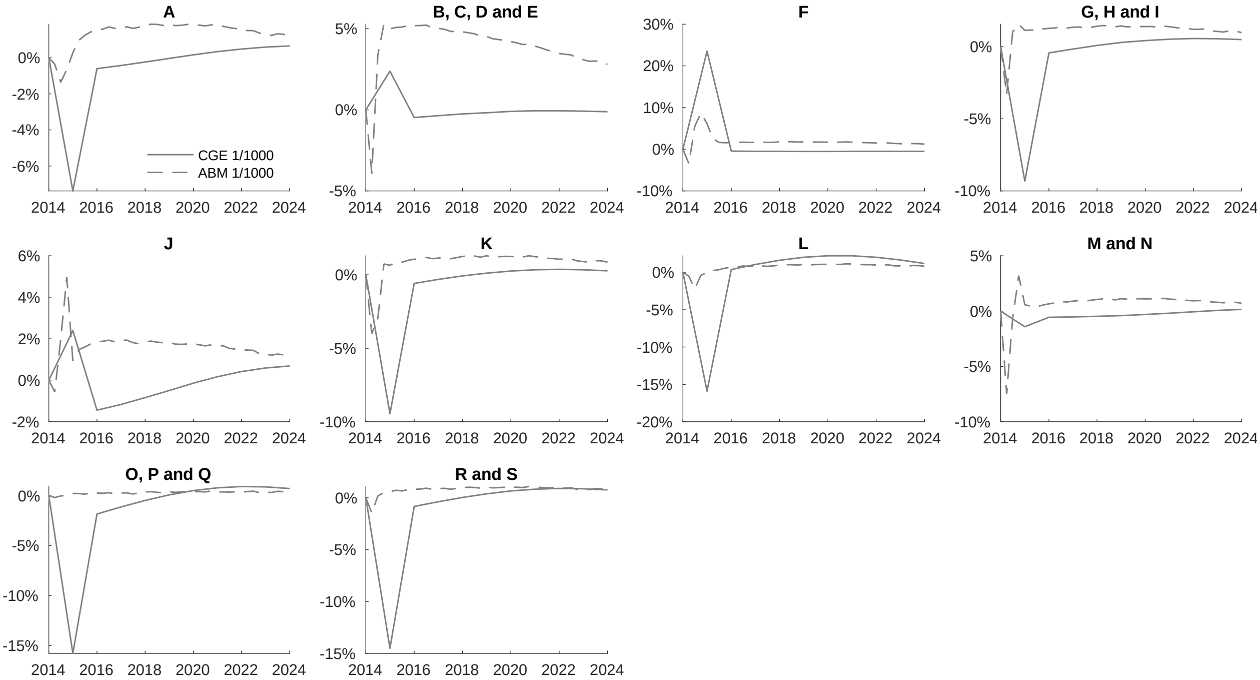

Figure 31: Comparison of CGE model and ABM. Changes in sectoral GVA relative to the baseline (current prices). GVA is shown for the sectors Agriculture, forestry and fishing (A); Industry (except construction) (B, C, D and E); Manufacturing (C); Construction (F); Wholesale and retail trade, transport, accommodation and food service activities (G, H and I); Information and communication (J); Financial and insurance activities (K); Real estate activities (L); Professional, scientific and technical activities, as well as administrative and support service activities (M and N); Public administration, defence, education, human health and social work activities (O, P and Q); Arts, entertainment, and recreation, as well as other service activities (R and S).

In Figure 32, the consequences for fixed assets as depicted for the total in the right graph of Figure 30, are displayed here differentiated for the respective production sectors. The results from the ABM reveal clear patterns across all economic sectors: after the initial destruction, reconstruction activities restore initial levels of fixed assets quickly. In contrast, fixed assets in the CGE model react more differentiated with respect to the sectors and do not always retrieve baseline levels. For example, while there is only a minor impact in the year of the flood damage in sectors A and J, fixed assets spike in the year(s) after the event before steadily decreasing over the investigated time horizon with no tendency of returning to baseline levels. A further group of sectors seems to be more strongly affected in the beginning after the flood, but tends to recover towards the end of the model time horizon. These sectors include the heavily affected real estate sector L, the publicly demanded services O, P and Q, and privately demanded services R and S, which can be explained by substituting investments in sectors unrelated to reconstruction for related sectors, such as sector F. Therefore, the construction sector shows a substantial increase of fixed assets in the years after the initial shock. Further sectors required in the reconstruction phase include industrial sectors (B, C, D and E) as well as technical and engineering services (M and N). Thus, these sectors experience damages to fixed assets of about -2% induced by the flood event with a quick recovery after the first year and even an overshoot of baseline levels. A similar effect can be observed for the financial and insurance sector (K) and the wholesale and retail trade, transport, accommodation and food service activities (G, H and I) levelling towards the end of the time horizon but below baseline levels.

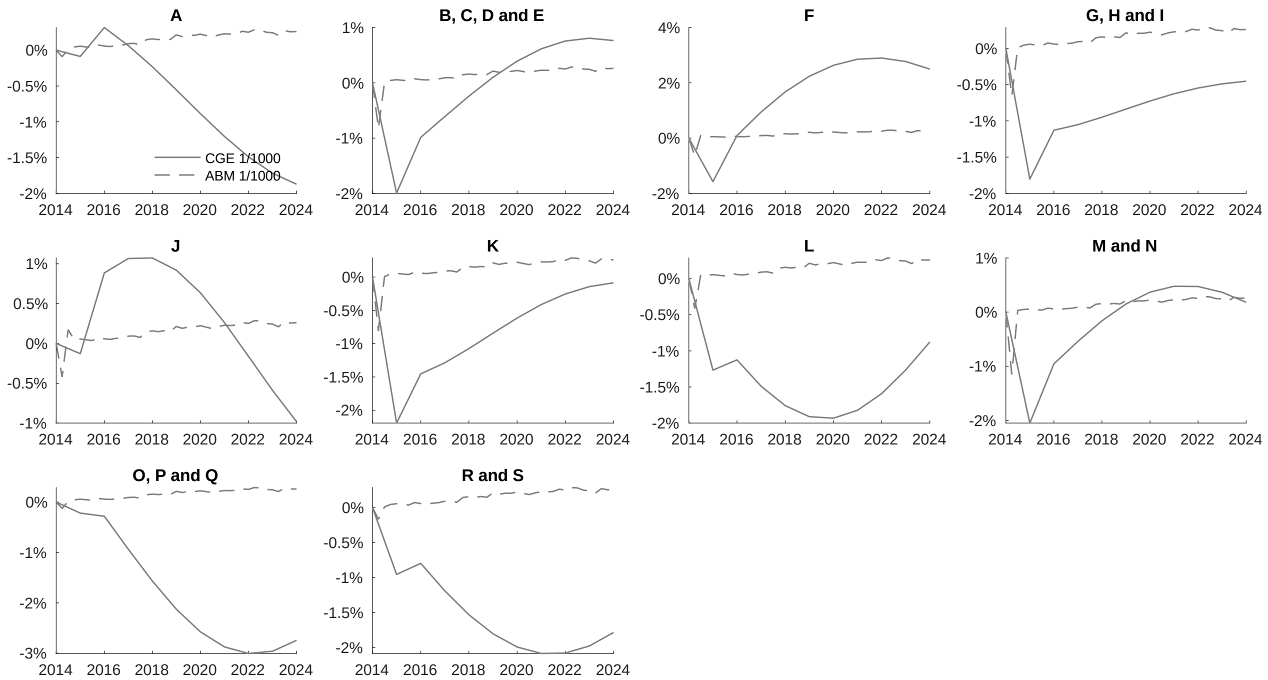

Figure 32: Comparison of CGE model and ABM. Changes in sectoral fixed assets relative to the baseline (current prices).

4. Conclusions and outlook

4.1. Key results and conclusions

The input output model showed the input sectors which are needed the most after a disaster event and therefore can be used as a proxy for determining key sectors in the reconstruction efforts. Transportation has been seen as especially important in nearly all scenarios. While such an analysis is useful for the short term (e.g. 1 year up ahead), it has to be embedded within other approaches that can take the indirect and also possible non-linear effects explicitly into account and also are able to provide estimates of long-term effects as well. One key result of this analysis is the finding that due to the differences of affected sectors for different impacts of disaster events, also the order of importance of different sectors may change as well. In other words, spatial explicit analysis of sectorial losses during a disaster event are key in using such an approach.

The key findings from the CGE analysis include that spatially explicit flood damages affect different household groups and different sectors differently. While capital owners and high income households are more strongly affected in the short term, low income households suffer more from increased price levels and capital scarcity in the long term. This demonstrates an indirect risk regarding distributional effects. 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. Wages also react more strongly than capital rents to flood damages, which results in an indirect risk for the public budget as labour tax income constitutes a major source of public income. As a consequence, also sectors in the public domain are severely affected by flood damage induced losses. This indirect risk can be measured as lost GVA relative to the lost capital stock. Besides publicly provided goods and services, this indirect risk is particularly high for sectors which produce goods and services for the final demand.

Key findings from the ABM are that moderate disasters do not always have a negative impact on economic growth, however very extreme disasters have pronouncedly negative economic effects immediately after the event and also in the long term. Similarly to the results from the CGE model, when applying the ABM we find that disaster losses differ substantially across industries and economic sectors

4.2. Outlook

In this report we have revealed important indirect risks, specifically distributional effects as well as sectoral indirect risks in terms of lost gross value added when indirect economy-wide effects are accounted for. Such information is very valuable for indirect risk management. Now decision variables are available on sectoral level which can be used to protect in a more targeted way. The next step is to find concrete indirect risk management options and measures.

To address model uncertainty, further modelling 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; i.e. the currently observed shortage of certain skills on the labour market). Further, the CGE model assumes full employment of labour, i.e. no short-term possibility to increase employment but rather that labour demand changes are reflected in the wage rate. Introduction employment effects might change the results. Further, the CGE model assumed that in all scenarios reconstruction can be completed within one year, which might not be the case for extreme events. Lastly, indirect risk management options other than market driven effects should be implemented in both the CGE model and the ABM. This will be done in the further stages of the project.

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Appendix

A.1 CGE model details

A.1.1 WEGDYN-AT model sectors and NACE correspondence

Table A 1: WEGDYN-AT model sector aggregates and correspondence to OeNACE sectors

Model sector	OeNACE	**Model sector**	OeNACE	**Model sector**	OeNACE	**Model sector**	OeNACE
AGRI	A 01	**MAME**	C 25	**TRWH**	G 46	**RADE**	M 72
FORE	A 02	**MAED**	C 26	**TRRE**	G 47	**ADVT**	M 73
FISC	A 03	**MAEL**	C 27	**LTRA**	H 49	**FREO**	M 74-75
FEXT	B 05-07; C 19	**MACA**	C 28	**WTRA**	H 50	**SRNT**	N 77
MEXT	B 08-09	**MAVE**	C 29	**ATRA**	H 51	**SLAB**	N 78
FOOD	C 10	**MAVO**	C 30	**STRA**	H 52	**TRAV**	N 79
BEVE	C 11 - C 12	**MAFU**	C 31	**POST**	H 53	**SECO**	N 80-82
TEXT	C 13	**MAOT**	C 32	**ACCO**	I 55-56	**PUBL**	O 84
CLOT	C 14	**MARE**	C 33	**SPUB**	J 58	**EDUC**	P 85
LEAT	C 15	**ELYs**	D	**CINE**	J 59	**HEAL**	Q 86
WOOD	C 16	**HEATs**	D 35	**BRDC**	J 60	**NURS**	Q 87-88
PAPE	C 17	**GAS_MDT**	D	**TELE**	J 61	**ARTS**	R 90
PRNT	C 18	**WATE**	E 36	**SITC**	J 62-63	**CULT**	R 91
CHEM	C 20	**WAST**	E 37-39	**SFIN**	K 64	**GMBL**	R 92
PHAM	C 21	**BUIL**	F 41	**INPE**	K 65	**SPOR**	R 93
PLAS	C 22	**CIEN**	F 42	**LEGA**	M 69	**ASSO**	S 94
GLAS	C 23	**CONT**	F 43	**CNSU**	M 70	**UREP**	S 95
META	C 24	**TRCA**	G 45	**ARCH**	M 71	**SOTH**	S 96

A1.2 Making investment shares endogenous

Step 1) PK-K relationship (capital price elasticity of supply)

As a first step we estimate the relationship between capital rents (PK) and capital (K) availability, using the CGE model in benchmark year. We increase capital endowment in the CGE model for all sectors stepwise by 5% until 150% (x-axis in Figure A1) and observe the associated change in capital rents (y-axis). We then use the following equation to estimate parameters:

$$PK = base * e^{(K * \exp)} \qquad (1)$$

With $base$ and $\exp$ being parameters coming from estimation. This relationship is used to mimic behaviour of investors, who would expect lower capital rents with increasing abundancy of capital.

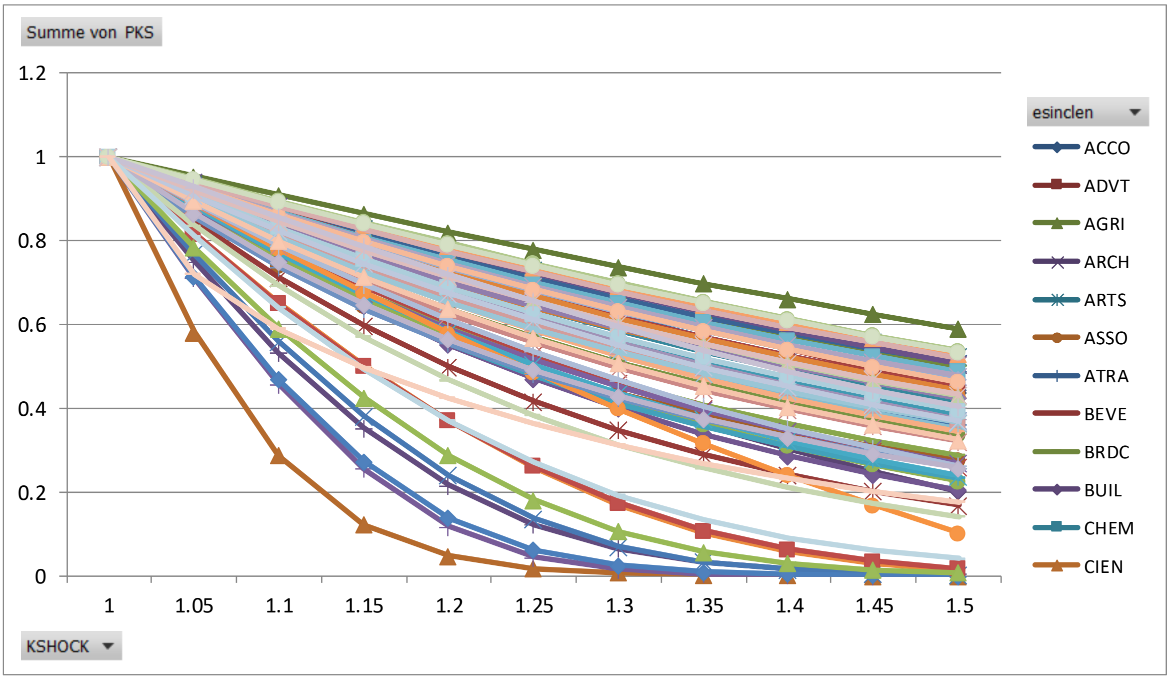

Figure A 1: Relationship between PK (y-axis) and K (x-axis) [not all sectors shown in legend]

Step 2) K-PK relationship

Transforming the relationship from (1) to

$$K = \ln(PK/base)/exp \qquad (2)$$

Eq. (2) gives how K is "driven" by PK. Intuition: The higher/lower the capital rent (PK) is, the more/less capital becomes available (i.e. is invested into this type of capital). This leads to a stabilizing effect. Put differently: How much should K be changed to, in order to reach PK=1 again (i.e. "benchmark optimality")?

$$Kredfact = 1 - \ln(PK/base)/exp \qquad (3)$$

Step 3) New K & INV levels and resulting investment shares

How much should new sectoral investment sum be, given economy-wide investment?

$$rdcdINV = (1 + Kredfact) * (INVtot * sctINVshr_p) \qquad (4)$$

With $INVtot$ being economy-wide investment of the period (which is determined endogenously according to fixed savings rate) and $sctINVshr_p$ being sectoral investment share of previous period.

This gives a hypothetical new sector-specific investment sum for all sectors (es). The hypothetical sum of investment over all sectors might not match with $INVtot$, so $rdcdINV$ is rescaled by the following factor

$$resclINV = INVtot / \sum_{es} rdcdINV \qquad (5)$$

New investment per sector is thus

$$newINV = rdcdINV * resclINV \qquad (6)$$

The sum of $newINV$ over all sector now matches $INVtot$.

The new sectoral investment share is then:

$$sctINVshr = newINV / INVtot \qquad (7)$$

This process leads to the following behavior: When capital rents are high/low, more/less is invested into this capital stock (strength is depending on price elasticity), thus more/less capital is available in next period, meaning that its capital rent goes down/up due to relative abundance/scarcity effects. This leads to a stabilizing effect in capital rents over time. Note that since the total amount of investment is given, the relative investment shares that materialize are subject to the price elasticity (expectation) and the price of the past. This means that if the capital rent (price) of a specific sector increases, its investment share not necessarily has to increase as well (even though there is an upward pressure), as other sectors' effects might be stronger and crowd out investment of this sector.

<u>Comparison of results of baseline and capital stock shock-scenario</u>

Figure A 2 shows that with endogenous investment shares the variation across sectoral capital rents is smaller than with exogenously given constant shares from the benchmark year (2014).

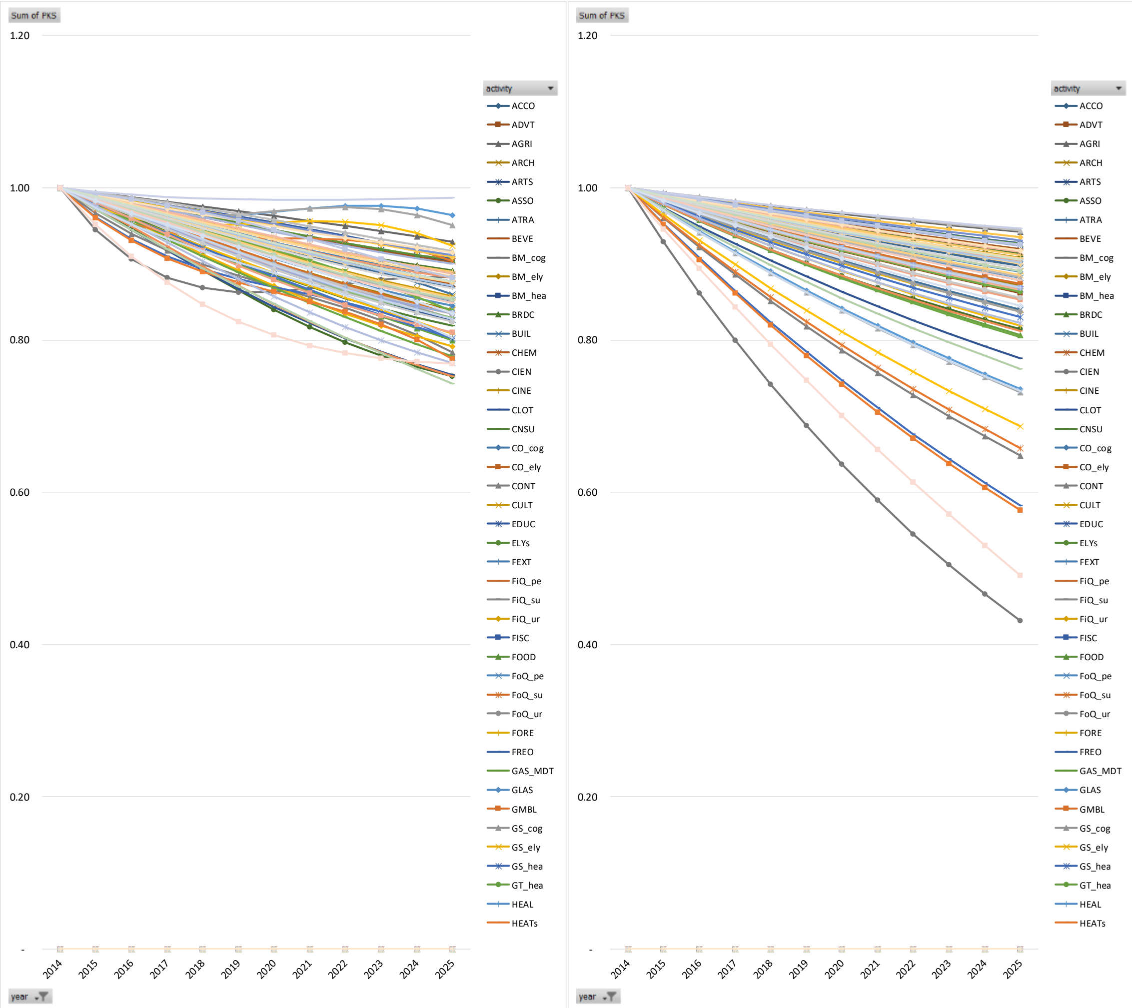

Figure A 2: Rental price of capital in baseline. Left: with endogenous investment shares; right: with exogenous constant investment shares.

A1.3 Additional results from the CGE model

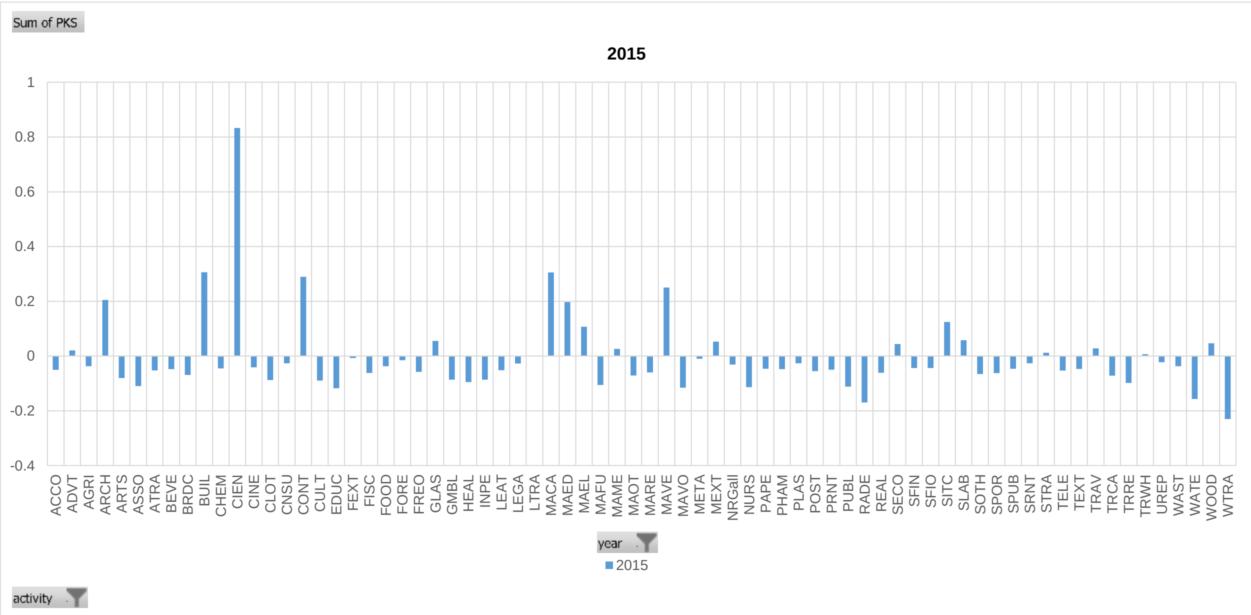

Figure A 3: Change in sectoral capital rents relative to baseline (year: 2015, scenario: 1/100-year event)

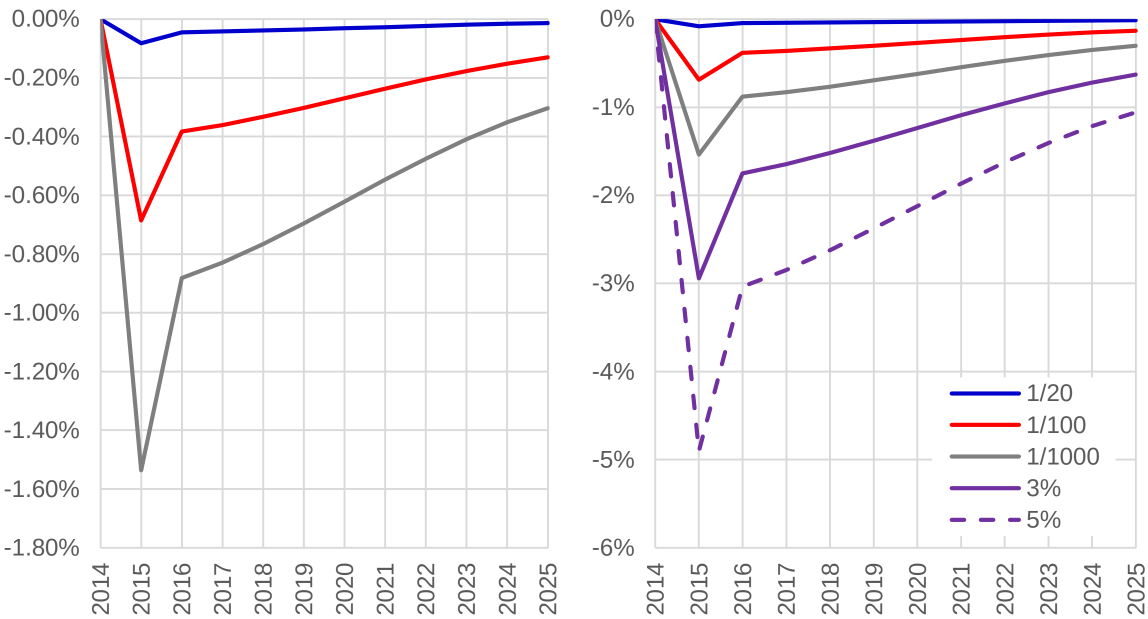

Figure A 4: Change in capital stock relative to baseline.