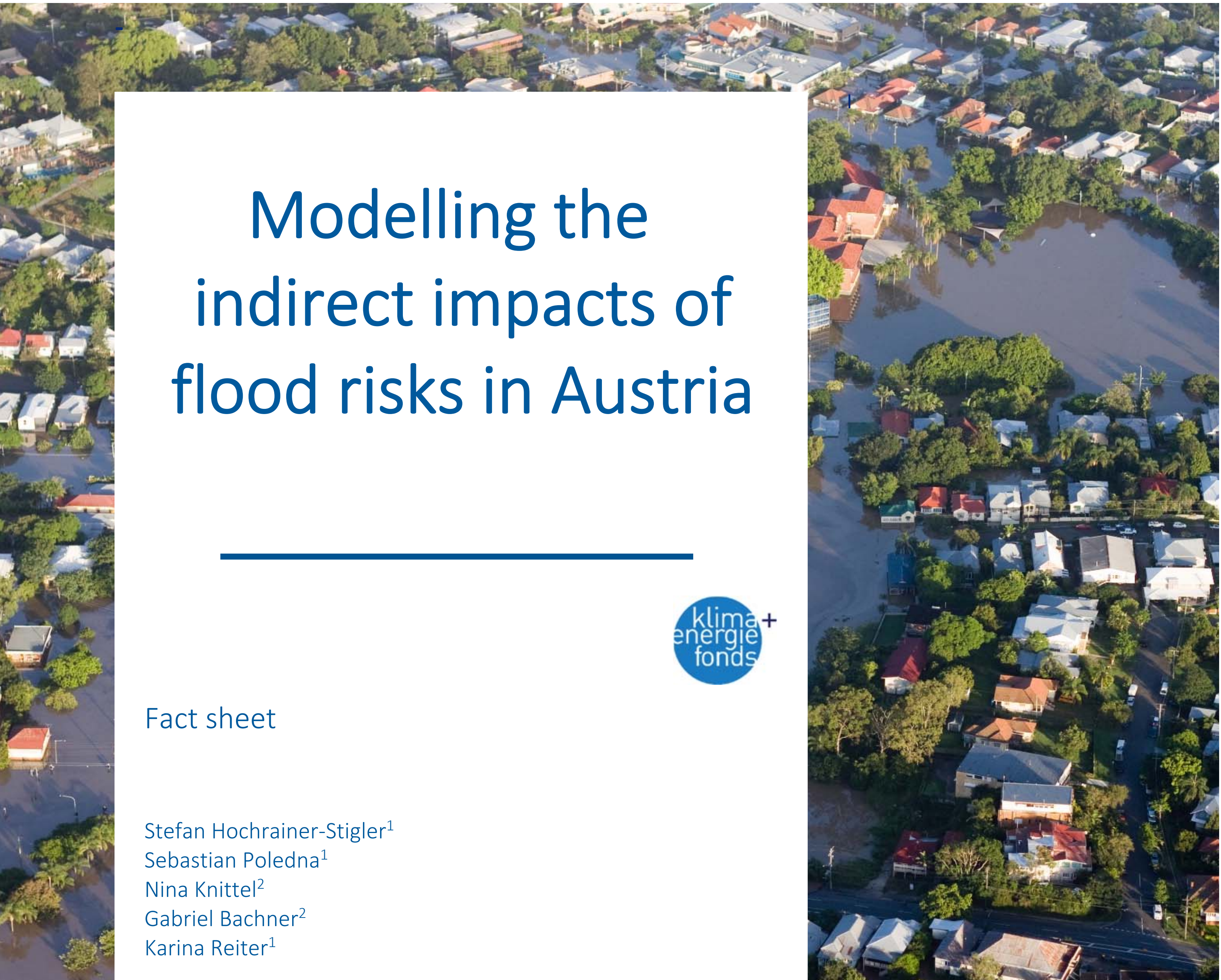

Modelling the indirect impacts of flood risks in Austria

Fact sheet

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Modelling indirect flood impacts and cascading risks

Due to increasingly complex economic networks and interdependencies, natural disasters can result in large ripple effects including business or supply chain interruptions, changes in economic productivity or increased indebtedness. These so-called indirect losses can amount to or even exceed direct damages (Koks et al. 2015; Dottori et al. 2018). In Factsheet 1 (Reiter et al. 2022), we discussed how indirect risks from floods are currently considered in the context of Austrian climate risk management strategies and how they could be proactively integrated on various scales. In this Factsheet 2, we present related modelling results from three highly detailed macro-economic models on indirect impacts due to large scale flooding in Austria. In more detail, we used a set of state-of-the-art economy-wide quantitative models – an input output (IO) model, a computable general equilibrium (CGE) model and an agent-based model (ABM) – to calculate economic losses and acquire a deeper understanding of indirect flood risks.

Direct risk of floods and indirect flood impacts

Flood risks and the ensuing damages cause direct as well as indirect effects. The latter describes flow-on effects of direct damages and include, for instance, increased debt, business or transport interruption (Hochrainer-Stigler et al. 2018). Due to increasingly intricate economic networks and interdependencies within them, indirect effects of floods (and other hazards) have increased in the last decades. Additionally, due to climate and demographic changes, damages from major flood events are expected to grow in the future. The extreme flood event in Austria in 2002 showed that these events do not happen in isolation but over large scales. Spatial dependencies during flood events, which can span several regions, need to be taken into account to avoid underestimating risks. This is especially important for indirect risk as the larger the direct losses (and the larger the number of people affected at once), the larger the likeliness that also indirect losses will occur (as such extreme events usually overburden agents to deal with them effectively, e.g. due to budget constraints).

In that regard, Schinko et al. (2017), Albrecher et al. (2020) and also the COIN project (Steininger et al. 2015) have suggested that a more appropriate method to estimate extreme flood risks for Austria is using a so-called copula approach, which can take spatial dependencies of hazard events explicitly into account. The copula approach is especially useful for analyses of large-scale extreme events on the country level (Hochrainer-Stigler et al. 2020), which is an essential prerequisite for a probabilistic macroeconomic analysis. Building on this work, we used a highly detailed exposure and hazard mapping approach to relate exposed assets to flood events. This was subsequently applied to distribute total losses due to a flood event to individual sectors according to the geospatial distribution of capital owned by non-financial and financial firms and by government entities. To understand the indirect risks for different flood loss return periods, we analyzed a range of different scenarios as depicted in Table 1. For example, a 20-year loss event is an event that happens, on average, every 20 years or with an annual probability of five percent (1/20). We also added less likely events, including the 100-year and 1000-year loss event as well as some very extreme ones, which we called Armageddon Scenarios.

Scenario	Total losses on the country-level (in constant 2015 million € or % of capital stock destroyed)	Description
1/20	€ 932	20-year loss event
1/100	€ 7,748 (0.7%)	100-year loss event
1/1000	€ 17,349 (1.57%)	1000-year loss event
Armageddon Scenario I	3%	1000-year loss event in all basins simultaneously
Armageddon Scenario III	17%	Half of all exposed assets destroyed

Table 1. Overview of some scenarios and corresponding loss levels analyzed.

In a next step, these losses were implemented in a highly detailed CGE model, an ABM as well as in an IO model. Details to each modelling approach can be found in Bachner et al. (2020). Here, we discuss each approach only briefly to set up the stage for the results.

Multi-model approach for indirect flood impact assessment

One of the main benefits of **IO models** is 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, the latter of which is used here as well. For a comprehensive review of current IO models for disaster risk analysis we refer to Galbusera & Giannopoulos (2018).

Using **CGE models**, one can explore economy-wide and indirect effects of localized "shocks" within a given economic system. Such models are usually based on input-output tables and thus capture interlinkages across all economic agents. However, as opposed to conventional input-output models, CGE models allow for non-linear reactions, i.e. for substitution processes within production and consumption as they are based on micro-economic theory. Specifically, they assume cost minimization in production and utility maximization in consumption, using production/utility functions calibrated to observed elasticities of substitution. The WEGDYN-AT model used in this analysis is a recursive-dynamic, multi-sector, small-open-economy CGE model calibrated to the Austrian economy. It builds on the multi-household version developed in Mayer et al. (2021) and was extended to cover sector-specific capital in the present project.

Furthermore, we use the **ABM** developed by Poledna et al. (2020), which includes all institutional sectors (financial firms, non-financial firms, households, and a general government). In a nutshell, the firm sector is composed of 64 industry sectors according to national accounting conventions and the structure of input-output tables, similar to the CGE model. Markets are fully decentralized and characterized by a continuous search-and-matching process that allow for trade and other 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. For that, the ABM follows the approach of Hommes & Zhu (2014), which has agents learn the optimal parameters of simple parsimonious Autoregressive AR(1) rules. The ABM used here was validated based on historical data by demonstrating comparable performance to standard DSGE and VAR models.

Key results

The IO model illustrated which sectors' inputs are most urgently required following a disaster event. Therefore, it can serve as a guide for identifying key sectors during the reconstruction period. In almost all scenarios, the transportation sector was found to be particularly important. Interestingly, the priority among sectors may change across different events as each event has different exposure levels and sectoral loss distributions. As a consequence, there are different key sectors for the reconstruction period for these scenarios. However, this type of analysis is valuable only for short-term periods of, for instance, up to one year. Thus, such modelling approaches need to be combined with others that can explicitly account for indirect and potential nonlinear impacts to provide assessments of long-term impacts.

The CGE analysis showed that spatially explicit flood damages have differential effects on economic sectors and household groups. In the short run, high-income households with higher capital assets are more severely affected while low-income households are burdened in the long run due to higher price levels from capital shortages (see Figure 1). This shows an indirect risk from flooding in terms of distributional effects. Another key finding is that the adverse changes in private consumption possibilities are accompanied by a reduction in the supply of public services, which is particularly relevant for and further increases the burden on lower income quartiles. This reduction is caused by income losses of the public sector, which consists of tax income from affected sources such as labor and capital. Hence, besides potential direct public expenditures such as compensation payments, the public budget is indirectly at risk from reduced income and therefore a tightened fiscal space. As a result, also sectors that produce goods and services for the public sphere are more strongly affected by flood damage-related losses.

Additionally, we measured indirect risks by determining how much a sector lost in terms of gross value added (GVA) in relation to the direct capital loss. Thereby we measured whether the direct damage to the sectoral capital stock is larger or smaller than the loss of sectoral GVA including economy-wide feedback effects. Our analysis showed that indirect risk is very high especially for sectors that produce goods and services for final demand as well as goods and services of the public domain. For some sectors, the lost GVA is 100-1,000 times higher than the direct damage due to economy-wide feedback effects. In contrast, some sectors show negative indirect risk values, i.e. they benefit from the economic shock. These are sectors which contribute to the reconstruction process after the shock (construction, buildings, manufacturing of cars, civil engineering etc.). The results give a detailed picture of sectoral winners and losers in regard to indirect risks due to a flood event. Therefore, they are especially useful for determining which sectors and possible instruments one should be looking at to reduce indirect risks.

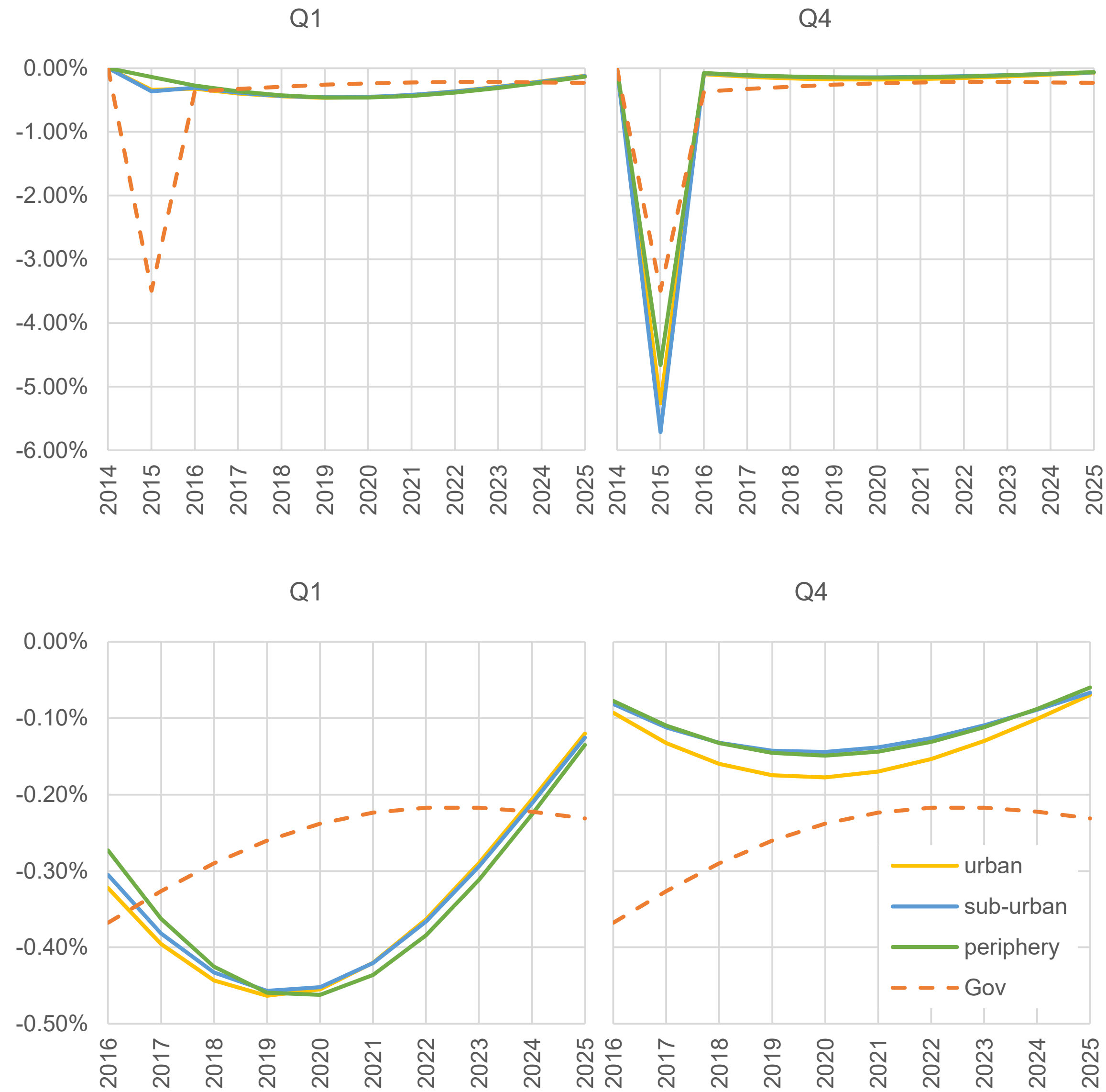

Figure 1: Percentage change in consumption quantities for the lowest (Q1) and the highest (Q4) income quartile across locations of residence (urban, sub-urban, peripheral) as well as changes in public service provision (Gov) relative to the baseline for scenario 1/100. Top: whole time horizon, including year of event. Bottom: post-event years only.

The ABM illustrated that a negative impact on economic growth is not necessarily a consequence of moderate disasters, while extreme disasters have a very negative economic impact both immediately after the event as well as in the long run. For example, our analysis demonstrated that the change in the unemployment rate is inversely correlated to economic growth and that the indirect economic effects after an extreme-disaster are qualitatively different from the moderate-disaster scenarios. With a 1000-year event, the real estate sector suffers substantially from the destruction of residential capital stock at the beginning. However, sectoral output soon surpasses its initial level due to reconstruction activities. The construction sector immediately profits from the reconstruction of dwellings and productive capital in the first year after the flood. This effect gradually wears off in the following years but remains at a slightly elevated level in the long run. In contrast, the restoration of productive capital takes more time. Similar to the results of the CGE model, the ABM shows that disaster losses vary significantly by industry and economic sectors, however, for a different time period (up to three years) and in more temporal detail (quarterly information is possible to gather).

A call for multi-model assessments for indirect risk

For several aspects, the CGE and the AB model showed different results. This phenomenon originates largely from the underlying assumption of whether the economy is supply- or demand-driven. 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, has to be financed by a reduction of other activities elsewhere in the economy. This in turn means that reconstruction does not stimulate the economy, but rather reduces productivity as the means for reconstruction crowd out otherwise more productive investment. Such an economic state would mirror the conditions of an economic boom phase, where the economy runs at its upper production limit. In contrast, demand-driven models, such as IO, post-Keynesian or AB models assume that the economy can grow by demand stimulus, e.g. for reconstruction. This assumption implies that (physical) production capacities are idle and can be activated by higher demand (e.g. financed by public debt).

It is not only these assumptions that influence the possible dynamics at hand which are relevant for indirect risk assessment, but also the timescale is of particular importance. While an IO model is appropriate for the very short term (up to 1 year), an AB model can also be used for the medium term (e.g. up to 3 years) with quarterly information available and a CGE model can take a long term perspective (e.g. up to 10 years or more into the future). With each of these models shedding light on some specific aspects of this complex issue, they can be seen as representing an ensemble of different perspectives. Consequently, all approaches presented have their value and applying only one of them to investigate indirect risks may inappropriately bias the view (Hochrainer-Stigler et al. 2020). Additionally, due to changing socio-economic conditions adaptive and iterative processes for the assessment of indirect risks are needed. A toolbox-based approach embedded within such a process is a promising way forward as it would enable to link methods, models and approaches in a way that highlights the complex nature of such kind of analysis and thus emphasizing the existence of multiple entry points to the management of indirect risks. In Factsheet 3, we discuss such potential interventions in more detail.

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