Robustness of the evaluation of indirect costs of natural disasters: example of the ARIO model

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Abstract

Given the interconnectedness of economies and the prevalence of just-in-time production processes, even small interruptions to production caused by natural disasters can lead to great indirect economic impacts. A substantial body of literature on this subject exists, notably with the help of input-output analysis, CGE and agent-based models. However, such models rely on parameters and data which are often unobserved empirically or estimated with wide margins of uncertainty. The reliability of these models is therefore difficult to assess. Here, taking the example of the July 2021 floods in Germany, we analyze to what extent the results of the ARIO model are robust to input data and parameter choices. The ARIO model is a widely used model in the literature, and has laid theoretical foundations for several other models. We conduct a sensitivity analysis by varying its key parameters, as well as the multi-regional input output tables which it uses as its main input data. For this, we develop a new resource-efficient Python implementation of the ARIO model, which enables a large number of simulations to be run. Our results show that the choice of the data source and parameters indeed heavily influences the outputs of the model. To ensure the robustness of their results, future studies on indirect economic impacts should incorporate several scenarios and employ data from various sources.

Keywords: Indirect economic risk, Input-Output models, Natural disasters

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1. Introduction

Natural disasters have long been recognized for their significant economic consequences. However, with the increasing frequency and severity of these events attributed to climate change, the issue has gained even greater prominence (Lange et al., 2020). Of particular concern is the interconnectedness of economies and the prevalence of just-in-time production processes, which has raised alarms about the potential for even minor disruptions in supply chains to have profound indirect economic impacts (Botzen et al., 2019; Hallegatte, 2015). Recent examples, such as the Suez Canal blockage (Lee and Wong, 2021), highlight the vulnerability of global trade and the subsequent implications for economic stability.

Although empirical studies have shed light on the global economic costs of natural disasters, precisely studying the characteristics of these costs remains challenging. One of the primary difficulties arises from the inherently indirect nature of the effects identified by models, making it problematic to isolate them in empirical data (Noth and Rehbein, 2019). Economic outcomes influenced by specific events can become entangled with numerous other factors, further complicating the attribution of changes to specific causes, particularly on a global scale. Furthermore, the complex nature of indirect effects often involves multiple rounds of economic activity and feedback loops that are challenging to quantify (Hallegatte, 2015).

In addition to these challenges, obtaining precise data on economic production for short-term analysis, below the yearly scale, can be arduous. Such data are often not readily available or may be subject to significant measurement error. Thus, there is an urgent need to enhance our understanding of the intricate economic effects of disasters and their impacts on supply chains, particularly within the context of climate change (Dasaklis and Pappis, 2013). To address these issues, various modeling approaches have been proposed, including Computable General Equilibrium (CGE) models (Rose et al., 2011), input-output analysis (Galbusera and Giannopoulos, 2018; Santos et al., 2014; Zeng et al., 2019; Zhang et al., 2018), and agent-based modeling (Inoue and Todo, 2019; Otto et al., 2017; Pichler and Farmer, 2021).

These models enable researchers to analyze the economic consequences of disasters in ways that would be difficult to achieve empirically, as well as enabling prospective analysis. They can be parameterized to reproduce existing empirical assessments of natural disasters, providing insights into associated impacts that may not be directly evaluated through empirical means. However, the reliability of the results generated by these models remains uncertain. Previous studies have demonstrated their sensitivity to the choice of parameters (Hallegatte, 2008, 2013; Koks et al., 2014; Ranger et al., 2010). To our knowledge, no study exists on the sensitivity to the selection of multi-regional input-output tables (MRIOT) from different sources. This contrasts with the fact that such tables serve as crucial input economic data for these models and that there is an increasing availability of them (Lenzen et al., 2012; Stadler et al., 2018; Thissen et al., 2018; Timmer et al., 2015).

In this study, we focus on the July 2021 floods in Germany (Section 2) as a case study to conduct an in-depth examination of the sensitivity of the Adaptive Regional Input-Output model (ARIO) (Section 3), which extends an input-output (IO) framework with additional adaptive dynamics (Hallegatte, 2013, 2008). This model is one of the most frequently used models in the literature on indirect economic impacts of disasters (Guan et al., 2020; Hallegatte, 2008; Koks et al., 2014; Ranger et al., 2010; Wang et al., 2020; Zhang et al., 2018), and it also serves as the foundation for several other models built upon its core concepts (Colon et al., 2019; Koks and Thissen, 2016; Otto et al., 2017; Shughrue and Seto, 2018). We explore a set of parameters and input data and compare simulation outcomes with existing empirical evidence of the economic consequences of the event (Section 4). Through this analysis, we demonstrate that a wide range of simulation outcomes can be achieved while remaining coherent with empirical data (Section 5).

To carry out this analysis, we developed a new open-source and resource-efficient Python implementation of the ARIO model, called BoARIO[1]. We first carry out simulations over a large set of parameters, and then incrementally reduce the set by excluding the values that produce results at odds with observation, such as an economic crash, near-collapse or indirect impacts amounting to values that would have been registered, in light of what actually occurred. We then evaluate the remaining uncertainty. Our results show that the reliability of the outcomes of ARIO are crucially determined by the quality and quantity of data available on the empirical consequences of the natural disaster. This highlights the uncertainty of the estimates obtained when using similar models in prospective studies (Koks et al., 2019; Shughrue et al., 2020; Willner et al., 2018), over events whose indirect consequences are by nature not observed. This also calls for improvements in the collection of detailed economic data after present day natural disasters, to better anticipate the economic cost of future ones in the context of climate change.

2. Case study : Floods in Germany, July 2021

Our case study is the flood event that affected Germany in July 2021. The flooding event resulted from a large-scale weather situation that affected Western and Central Europe from 13 to 15 July 2021. This flood is considered to be the worst flooding disaster in Germany since the Hamburg storm surge of 1962. It primarily affected the federal states of Rhineland-Palatinate and North Rhine-Westphalia. The disaster also resulted in significant damages in Bavaria and Saxony. The event claimed the lives of more than 180 people, making it one of the deadliest natural disaster in Germany since 1962 (Copernicus, 2021; Lehmkuhl et al., 2022). Correlation between climate change and the occurrence of this event have been established in (Kreienkamp et al., 2021). They show the probability of occurrence to be from 1.2 to 9 times more likely with climate change.

This flood has also been identified as the costliest single event in post-war history in Germany: the direct financial damage caused by the flooding estimated to be around €33.4 billion, €14 billion of which are attributed to households (BMI and BMF, 2022; Munich Re, 2022).

In this study, we use these figures as input to simulate the indirect economic damages of the floods with the ARIO model. More precisely, we express the direct damages as a share of the 2021 Gross Value Added (GVA) of Germany or of each affected Lander (depending on the geographic resolution of the MRIOT we use), and distribute these damages to the sectors of the different MRIOTs, using their contribution to the affected regions GDP as a proxy.[2] Detailed distribution

[1] https://github.com/spjuhel/BoARIO

[2] Later in the article, we compare the simulated indirect economic impact for different MRIOTs based on different years. As the German GVA is different for each year and in order to get comparable results, we suppose that the direct damages are constant relative to the size of the economy (i.e. we suppose that the direct damages amount to the same share of the GVA in all our simulations).

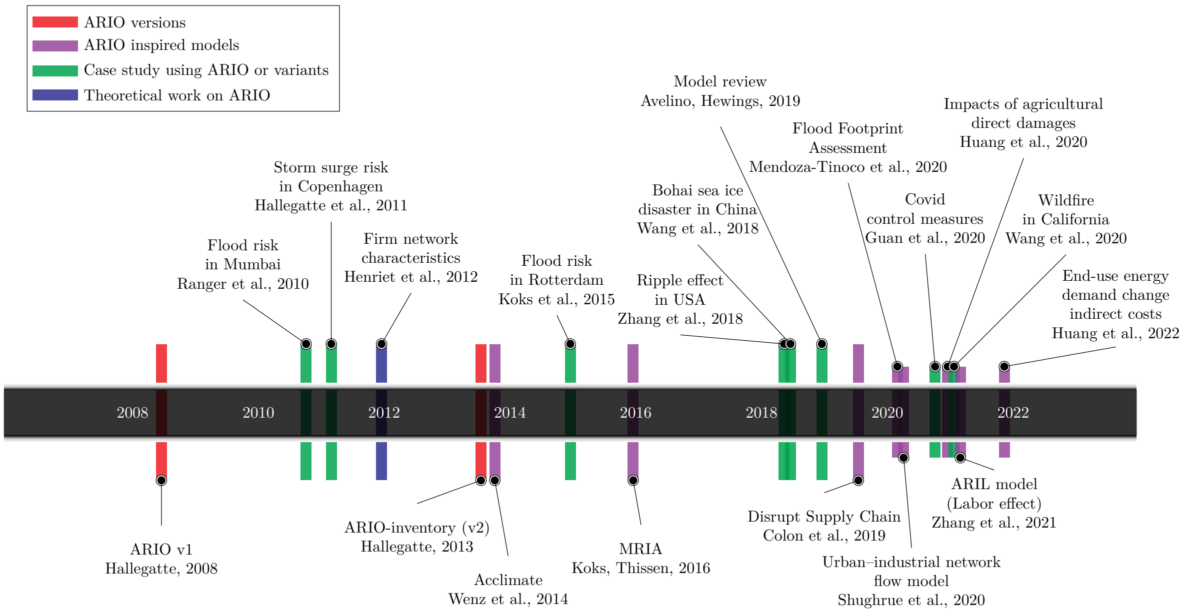

Figure 1: Chronology of the literature related to the ARIO model.

choices are available as files in the supplementary materials.

Using a static IO approach (Sieg et al., 2019), based on 2013 Germany National IO table, Trenczek et al. (2022) estimated that the floods lead to indirect economic approximately equal to €7.1 billion (21% of the direct damages), due to interruptions to supply chains and losses in industrial production. We use this estimation as a benchmark later in the paper (Section 5.2).

3. The ARIO Model

3.1. *ARIO in the indirect impact literature*

The ARIO model was first developed by Hallegatte (2008) to study the economic consequences of hurricane Katrina in Louisiana. It was later improved by Hallegatte (2013) to integrate inventory mechanisms and has, since, been used in close to 20 articles studying the indirect economic costs of various natural disasters (or economic shocks in general). Recently, Huang et al. (2020) used it to assess the economic cascading effects of future climate change on agriculture in China. Mendoza-Tinoco et al. (2020) assessed the economic consequences of the 2009 Central European floods using the ARIO model coupled with an inequalities model and found that developed economies suffered more from indirect costs than less developed ones. Guan et al. (2020) analyzed the supply-chain effects of a set of idealized COVID19 lockdown scenarios. The mechanisms of ARIO were also used as theoretical foundations for several other models, such as Acclimate (Otto et al., 2017), the MRIA model (Koks and Thissen, 2016) or the hybrid urban-trade model developed by Shughrue et al. (2020); Shughrue and Seto (2018). Figure 1 presents a comprehensive chronology of studies using or related to ARIO.

3.2. Brief description of the ARIO model

In ARIO, the economy is modelled as a set of economic sectors and a set of regions based on multi-regional input-output tables (MRIOT). In the following, we call an industry a specific (sector, region) couple. Each economic sector produces its generic product and draws inputs from an inventory. Each industry answers to a total demand consisting of a final demand (households consumption, government expenditures and capital formation) coming from all regions (i.e. both local demand and exports) and an intermediate demand[3] (trade between firms represented by inventory resupply). Additionally, total demand can also include another demand tied to the rebuilding process (Section 4.2.3 and Appendix A.1.2).

The model describes how exogenous shocks propagates across the economy at each time step (a day in this study). Such a shock is defined, for a set of industries, by the amount of production capacity lost and by how the model recovers from the shock. Affected industries regain their production capacity either by:

(i) An exogenous recovery function governed by a characteristic time τ_{recover}.
(ii) The endogenous answer to a additional rebuilding demand. In this case, industries answer the remaining rebuilding demand at each step at a rate of $\frac{1}{\tau_{\text{rebuild}}}$.

Following a shock, the imbalance between production and demand is resolved by a proportional rationing scheme, which then leads clients (both industries and households) of affected industries to not receive the totality of their orders. Industries can buffer these unfilled orders with their inventories of inputs and increase their resupply demand, possibly shifting to other suppliers. Currently, households simply register the loss as final consumption not met. During the simulation, industries adjust their production and orders based on total demand. When total demand is higher than current production, industries can increase their output at a characteristic rate of $\dfrac{1}{\tau_{\text{alpha}}}$ up to a maximum overproduction factor α_{max}. In ARIO, overproduction comes at no cost for the economic agents: it is limited by the fact that it is not an instantaneous process and that it cannot exceed α_{max}.

Production level is also constrained by the state of inventories. At a given step, inventory size of an input is defined as the number of days that an industry can sustain its current production level without receiving additional supplies of said input. Therefore, inventory goals are set relative to both the initial inventory values and the current production capacity.

Notably, if the inventory of an input appears insufficient to maintain the current production level for a goal duration, an industry will enter "*shortage*": it will reduce its production output so that its current inventory becomes sufficient to supply production for the given duration. Parameter ψ, which may range from 0 to 1, governs how industries treat their inventories when they are below objective. ψ represent the share of inventory objective actually required to not enter "shortage regime". For example, at a value of 0.9, production would only be reduced when the inventory of an input falls below 90% of the goal.

[3]The terms "intermediate demand" and "intermediate orders" or just "orders" will be used without distinction in the following.

As a consequence, if ψ is close to 1, shortages and bottlenecks are more likely to appear, or to appear sooner. In that sense, inventories allow ARIO to be more flexible than pure IO models, but also create the possibility of a drop in production output due to shortages.

For an in depth description of the model, please refer to Appendix A.

4. Overview of the analysis

We study ARIO's sensitivity to both the economic data used as input (the MRIOTs) — as multiple readily available sources exist, and to the parameters of the model. To do this, we first run simulations of the indirect cost of German 2021 floods using 3 different MRIOTs (Section 4.1), and a wide range of values for the parameters (Section 4.2). Section 4.3 presents the outputs of the model that we analyze. To get meaningful estimates of the uncertainty of the model, we then reduce the set of parameter values by excluding those that produce results at odds with empirical observations (Section 4.4).

4.1. Multi-Regional Input-Output tables and inventory sizes used as inputs

Input-Output tables. We use three different MRIOTs sources for this study, namely EXIOBASE 3, EUREGIO and EORA26 (see table 1). We choose these three MRIOTs for their specificities: EXIOBASE 3, for instance, has a very precise typologies of sectors, whereas EORA26 contains data for almost all countries. EUREGIO, for its part, has a sub-national geographic resolution for the EU. These characteristics are summarized in Table 1. In addition, we compare results using both year 2000 and 2010 (which is the largest gap in time common to all three MRIOTs), to assess how this influences the results.

A comparison of the technical coefficients matrix of these MRIOTs, which can be considered as a normalized representation of economic structure, is presented in Appendix C. The figures show substantial variations in the relative differences between technical coefficients across the different MRIOTs, spanning a range of 10 to 1000. While part of the variations can be attributed to dissimilarities in the composition of the aggregated sectors for the different MRIOTs (notably the "Other" sector), there are variations exceeding a factor of 10, even among sectors that are expected to be closely aligned across MRIOTs, such as the "Construction" and "Agriculture" sectors. Discrepancies between two consecutive years within the same MRIO framework are shown for EXIOBASE3. As anticipated, variations in technical coefficients occur less frequently when comparing two years of the same MRIOT, especially when looking at the domestic trade links. However, some international trade connections shift by factors ranging from 5 to 1000, notably the "Agriculture" input for "Construction" and "Energy and Utilities and Mining" sectors. These findings underscore the nontrivial nature of MRIOT selection.

Inventory sizes. We set the initial inventory size for all inputs to 90 days of pre-disaster economic activity, and the characteristic time for inventory resupply (Section 3.2) to 60 days, same as in Hallegatte (2013). We chose not to vary these parameters: a sensitivity analysis considering identical values for all sectors already exists in Hallegatte (2013), hence further analysis would require to define per sector values which was not computationally feasible in the scope of this study.

We also define a list of sectors which we consider non-constraining inputs in the short term (i.e. a shortage of these inputs has no effect on production capacity) :

- Activities of membership organization n.e.c.
- Extra-territorial organizations and bodies
- Financial intermediation, except insurance and pension funding
- Insurance and pension funding, except compulsory social security
- Real estate activities
- Recreational, cultural and sporting activities
- Activities auxiliary to financial intermediation

We estimate productive capital per industry by adapting the ratios of *capital to value added* used in Hallegatte (2013) to the EXIOBASE 3 sectors. The full details of these different choices are available for each MRIOT in files given as supplementary materials.

Name	**Number of sectors**	**Number of regions**	**Other characteristics**
EXIOBASE 3 (Stadler et al., 2018)	163	49 = 44 Countries + 5 rest of the world regions	Basic prices, 10^6€
EUREGIO (Thissen et al., 2018)	14	264 = 247 UE NUTS2 regions + 16 Countries + 1 Rest of the world	WIOD based, with NUTS2 regional disaggregation for EU, 10^6€
EORA26 (Lenzen et al., 2012)	26	189	Basic prices, 10^3\$

Table 1: MRIOT used in this study and their specificities

4.2. Parameters choices

4.2.1. Overproduction pace

This parameter determines how an industry can ramp up its production when total demand is higher than current production level. It is a measure of the time it takes for the industry to respond to the scarcity of goods. The magnitude of this parameter is linked to a scarcity index, meaning that, as the gap between production and demand widens, the industry accelerates its overproduction (See Appendix A.1.2).

The most common value for this parameter in the recent literature is 365 days (Guan et al., 2020; Koks et al., 2014; Hallegatte, 2013), which implies that it takes approximately one year for the industry to reach maximum overproduction. Previous studies used a value of half a year (Ranger et al., 2010; Hallegatte, 2008; Wu et al., 2011). We broaden the range of values for this parameter by including faster and slower pace, hence testing the four following values: 90 days, 180 days, 365 days, and 530 days.

4.2.2. Inventory heterogeneity

As we describe in Section 3.2, ψ parameter governs how industries consider the state of their inventory of inputs sufficient relative to their current level of production. If we distinguish between industry level (branches) and firms that compose them, ψ can also be thought of as the degree of heterogeneity and possible substitution between firms belonging to an industry:

- If ψ is close to 0, an inventory reduction in an industry is homogeneously distributed among its firms: inventory reduction impacts industry production only if it is large enough to affect a sufficiently large part of the firms.
- If ψ is close to 1, an inventory reduction in an industry is concentrated in a few firms and forces them to stop producing which directly impact production on the industry level.

Hallegatte (2013) evaluates his model sensitivity to ψ on five different values: 0.5, 0.7, 0.8 0.9 and 1 and shows the model to be highly sensitive to this parameter. As 0.5 and 0.7 values show no forward propagation of the initial shock, we assume evaluating for a lower value is not necessary. Moreover, in the same study, he suggests that for the case of a region being affected in a large economy, ψ would tend to be larger. Hence, in our analysis, we investigate the effects of the following ψ values: 0.5, 0.8, 0.85, 0.90, 0.95, 0.97 and 1.

4.2.3. Recovery/Rebuilding scenario

We also consider two options for the recovery of destroyed productive capital:

Recovery case Entirely exogenous recovery.

Rebuilding case Endogenous recovery through the answer to a rebuilding demand equal to the direct damages.[4]

We compare these two cases, as both exist in the literature (e.g., Wang et al. (2020) and Koks et al. (2014)), and to our knowledge, no study exists that compares both scenarios.

Furthermore, some natural disasters can affect production capacity only temporarily without requiring productive capital to be rebuilt. As well, the need for rebuilding, when required, may not be strictly equivalent to the direct damages, as some destroyed elements may not be reconstructed. Our two scenarios provide insights on how considering a rebuilding demand or not affect results.

In both cases, we also evaluate the sensitivity to the temporal dimension of the recovery process. We consider multiple characteristic periods[5] ranging from three months to two years. For the recovery case (no rebuilding demand) we also consider the sensitivity to the shape of the recovery curve (linear or S-shaped).

Note that we do not make any assumptions about the likelihood or validity of the considered scenarios for the chosen case study. Rather, this study serves as a theoretical exploration of the sensitivity of the economic model to different recovery and rebuilding scenarios.

[4] See Appendix Appendix A.1.2 and supplementary materials for details on how this demand is distributed among sectors.

[5] For the recovery case, a characteristic period of $\tau_{recover}$ days means that productive capital is recovered in approximately $\tau_{recover}$ days (depending on the recovery curve). For the rebuilding case, it means that $1/\tau_{rebuilding}$ of the remaining rebuilding demand is ordered at each step.

4.3. Outcomes of the model

We look at the total net production change from baseline (no event) over a two-year period. This time-frame allows for the return to equilibrium in all simulations and corresponds well to the temporal scope of the ARIO model mechanisms.

To facilitate comparison between the different MRIOTs, which encompass varying sets of regions and sectors (ranging from 163 sectors in Exiobase3 to 14 in EUREGIO), we aggregate the results to a common set of six regions and six sectors:

- `DEU`, `FRA`, `CHN`, `USA` and a rest of the world `ROW` region (i.e., the affected region, a geographically close region, two geographically far and major economies, and the rest of the world)
- `Agriculture`, `Construction`, `Energy and Utilities and Mining`, `Manufacture`, `Sales`, `Transports and Services`, `Others`

Our analysis primarily focuses on the region directly affected by the natural disaster, Germany. To facilitate comparison with existing literature, we express indirect damages as a share of the direct damages. Additionally, when comparing the impacts across different sectors, we express the indirect damages as a share of the initial production level. This approach allows us to gauge the relative severity of indirect damages within each sector.

4.4. Defining a subset of parameters range coherent with empirical data

Not all parameter choices lead to results which seem coherent with the reality. As our objective is to estimate the reliability of ARIO results in a situation similar to a typical academic research project, we remove from our input parameter set the values which lead to indirect economic costs at odds with empirical observations (such as a sudden collapse of the whole German economy after the floods) or with the literature.

More precisely, Table 2 shows the ratio of indirect losses over direct damage in several studies on indirect economic losses using either ARIO or a different methodology. Our criterion for considering indirect losses to be unrealistic is that they exceed direct damages by more than a factor of five, corresponding to the highest estimate we found in the literature (Carvalho et al., 2020)[6].

5. Results

Section 5.1 presents the parameters sets that are removed when we follow the approach described in section 4.4, and sections 5.2, 5.3, 5.4 and 5.5 examine the variation in results.

In the following, we express indirect losses relative to the direct damages or relative to yearly production when comparing impacts on the sector level. Note that, as the net change can be positive (production gains compared to baseline), we will use positive values to designate gains and negative values for losses.

[6] To our knowledge these values have not been validated using quantitative empirical data, thus cannot be used to validate results in a strict sense. However, all these studies do agree, that indirect losses and direct losses are of a similar order of magnitude.

Study	Method	Direct damages estimate	Indirect damage estimate	Ratio indirect/direct
(Hallegatte, 2008)	ARIO v1†	$107 Billion	$42 Billion	39%
(Ranger et al., 2010)	ARIO v1	$1500 Million	$425 Million	28%
(Hallegatte et al., 2010)	ARIO v1	€1700 - 14500 Millions	€14 - 2000 Millions	0.8% - 13%
(Wu et al., 2011)	ARIO v1	CNY 749 Billion	CNY 301 Billion	40%
(Hallegatte, 2013)	ARIO v2	$63 Billion	$11 Billion	17%
(Koks et al., 2014)	ARIO v2	€36.1 Billion/year	€23.4 Billion/year	64%
(Koks et al., 2019)	MRIA	Mean ratio of 50% increasing to 80% in the future††		
(Mendoza-Tinoco et al., 2020)	Flood Footprint Assessment model	-	-	150% - 500%
(Tanoue et al., 2020)	CGE	$14.7 Billion	$10.6 Billion	72%
(Trenczek et al., 2022)	Gosh IO model	€33.4 Billion	€7 Billion	21%
(Carvalho et al., 2020)	CGE	0.1% GDP growth	0.5% GDP growth	500%

Table 2: Indirect over direct damage ratio in the literature.

[†] We consider the first-order estimated annual output losses (EAOL) of the study which designate indirect impact of events on the impacted region.

[††] ARIO v1 designate the version presented in (Hallegatte, 2008), while ARIO v2 designate the updated version of (Hallegatte, 2013).

5.1. Restricting the input parameters set in accordance with existing literature

When we look at simulations where indirect losses are more than five times the direct losses, (corresponding to the previously defined criterion), we find that such indirect losses only appear when all the following is true:

- Rebuilding demand is considered.
- Rebuilding time is under a year (six and three month).
- ψ is at least equal to 0.95
- Overproduction pace is low enough (the precise value depends on rebuilding time and ψ)

A list of the corresponding sets of parameters is shown in Table 3. Following our criterion, we remove all of these sets from the results, which represents about 10% of the initial sets.

Ψ	**Recovery time**	α **and** τ	**Rebuilding demand**
1	all values under 730 days	all values	yes
0.97	90 days	all values	yes
0.97	180 days	all values strictly greater than 90 days	yes
0.95	90 days	all values strictly greater than 90 days	yes

Table 3: Set of parameters removed after selecting simulations with indirect losses less than 5 times the direct damages.

5.2. *Global sensitivity*

Here, we examine the spread of our results after removing the parameter sets previously described. We conduct our assessment by observing the total and per sector production change in Germany two years after the event, for all remaining simulations.

5.2.1. *Aggregated impacts*

Figure 2 presents the simulated aggregated production change, for the different MRIOTs used. Total production change ranges from about -250% (i.e. losses) to +40% (i.e. gains) of the direct losses. However, we find that more than 90% of the results fall between -40% and +10% of the direct losses. In the recovery case, we consistently observe negative impacts, comprised between -50% and -10% of the direct losses, a majority of results being lower than the -21% found by (Trenczek et al., 2022). When considering rebuilding demand, we find a mix of positive and negative impacts across all MRIOTs as well as a much wider range of impacts (from -280% losses to +34% gains). The choice of the year of MRIOT data used (2000 or 2010) shows noticeable change in the results, mainly for EUREGIO and in simulations with rebuilding demand (where negative extremes shift from -134% to -173% when using the 2010 data). This is also the case, but to a lesser extent, for the EORA26 MRIOT in both simulations with and without rebuilding demand (negative extremes shift from -45% (2000) to -40% (2010) without rebuilding demand, and from -250% (2000) to -280% (2010) with rebuilding demand). Results for EXIOBASE 3 deviate by less than 2% when changing the year, both when considering and not considering rebuilding demand.

When not considering rebuilding demand, the sensitivity to MRIOT choice does not change the results by more than 5%. Highest losses by MRIOT are -49% (EUREGIO 2000), -47% (EORA26 2010), and -40% (EXIOBASE3 2010), and average results are comprised between -28% (EORA 2010) and -23% (EXIOBASE 3 both years). Minimum losses (no simulation results in gains in this scenario) differ by at most 3% (-13% for EORA 26 2010 and -10% for EXIOBASE3 both years). Conversely, when considering a rebuilding demand, results are more sensitive to the MRIOT used. For instance, maximum gains for EUREGIO 2000 are 26%, while they amount to 34% for EXIOBASE 3 2010. Third quartile is respectively at 10%, -2% and -18% for EXIOBASE 3, EORA26 and EUREGIO. Across both years, average results are respectively at -11%, -31% and -48% for EXIOBASE 3, EORA26 and EUREGIO and first quartile is -32% for EXIOBASE 3, -47% for EORA26 and -67% for EUREGIO.

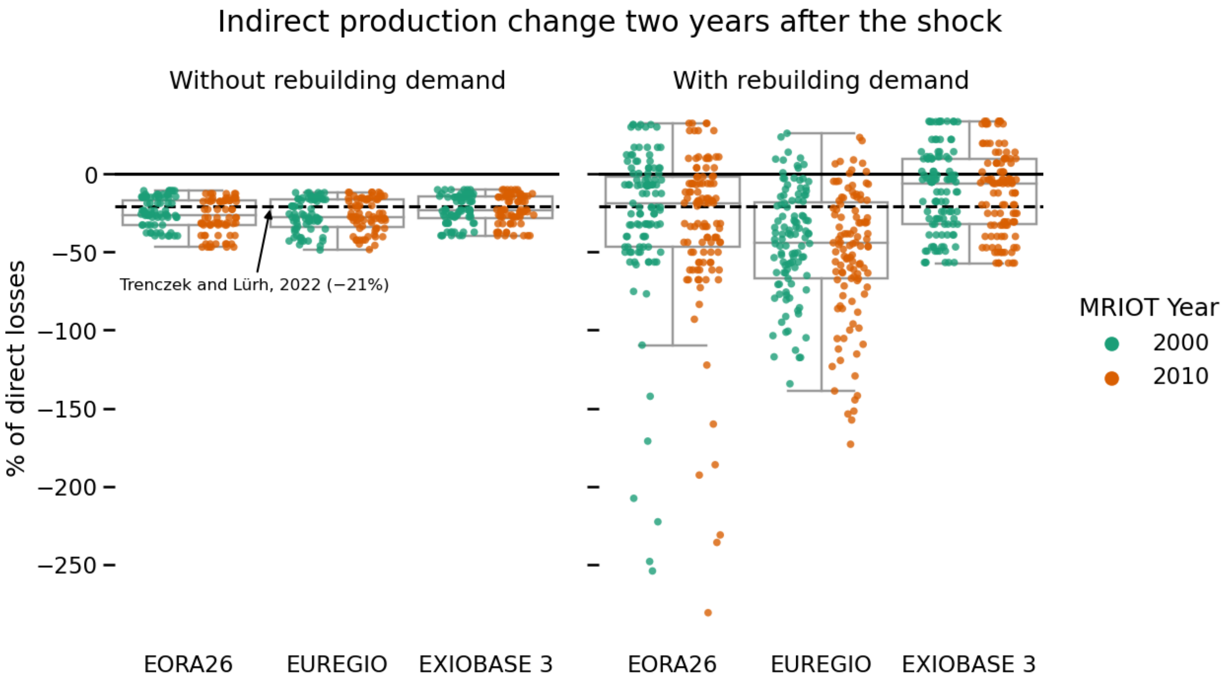

Figure 2: Comparison of aggregated production net cumulative change between the different MRIOTs after applying selection criterion. Results are expressed as a percentage of the direct damages. Each dot represents a different simulation. Color indicates the year of the MRIOT used. The boxplot shows the 25% and 75% quartiles and whiskers shows 99% of the distribution. The left side shows simulations for the recovery case, whereas the right side shows simulations for the rebuilding case. The dashed line shows the indirect losses estimated in (Trenczek et al., 2022).

In the simulations with rebuilding demand, outcomes are predominantly related to the pace of the rebuilding process (B.9). Notably, when associated with high values of ψ, a rapid path (3 months) tends to lead to shortages, thereby driving the occurrence of important negative impacts. On the other hand, longuest rebuilding paths (2 years) induce negative impacts from the prolonged reduced production and although less frequent, shortages can also manifest in this scenario. Conversely, rebuilding paths that do not lead to shortages, or only to marginal ones, generate production gains. These gains are driven by the demand generated through the rebuilding process.

Furthermore we observe that, with rebuilding demand, the variation in results between different MRIOTs becomes more pronounced for sets of parameters which lead to important negative indirect impacts. This indicates the sensitivity to both the chosen parameters and the specific MRIOT employed, increases when considering rebuilding demand and making pessimistic assumptions on the parameters. This observation echoes with the non-linear relationship between indirect losses and direct losses found by Hallegatte, 2013: given a specific direct shock and a set of assumptions (e.g., parameter values) that give rise to indirect losses at a magnitude equal to or surpassing that of the direct losses, even minor adjustments in these assumptions lead to greater changes in indirect losses than with more optimistic assumptions.

Figure 3: Comparison of per sector production net cumulative change between the different MRIOTs after applying selection criterion. Values are expressed as a percentage of the yearly production of each sector. Color indicates the MRIOT used. Boxplot shows the 25% and 75% quartiles and whiskers shows 99% of the distribution. The left side shows simulations for the recovery case, whereas the right side shows simulations for the rebuilding case.

5.2.2. Per economic sector impacts

Next, we examine the per-sector production changes (Figure 3). In the absence of rebuilding demand, all sectors except the "Construction" sector, experience a decline in their yearly production ranging from less than 0.01% to 0.3%. Differences in average results between MRIOTs are less than 0.03%. We observe a greater difference for the "Construction" sector which declines at most by 0.03% for EORA26 and EUREGIO 3, and by 0.4% for EUREGIO.

Conversely, when we consider the rebuilding demand, the overall range of outcomes for each sector within each MRIOT significantly widens. For instance, the "Manufacturing" sector has maximum losses reaching 1.1% and maximum gains of 0.2%, as opposed to the narrower range of 0.2% and 0.05% observed without considering rebuilding. Moreover, disparities in outcomes between sectors across different MRIOTs become more pronounced. For instance, using the EUREGIO MRIOT, the "Agriculture" and "Other" sectors exhibit results ranging from -1.5% to -0.02%, whereas the range narrows to -0.26% to 0.06% when employing the EXIOBASE 3 MRIOT. On average, losses per sector are comparable to, or greater than, those obtained without accounting for rebuilding demand, with the notable (and expected) exception of the Construction sector, which registers an average gain of 0.6%, due to the fact that the rebuilding demand targets mostly this sector. In some simulations, the "Manufacturing", "Sales, Transports and Services," and "Agriculture" sectors, see modest production gains (under 0.5% of yearly production).

Figure 4: Influence of the occurrence of shortage on results. Results are expressed as a percentage of the direct damages. Color indicates if a shortage happened during the simulation. The left side shows simulations for the recovery case, whereas the right side shows simulations for the rebuilding case. Boxplot shows the 25% and 75% quartiles. The dashed line shows the indirect losses estimated in (Trenczek et al., 2022).

5.3. *Shortages in the ARIO model: occurrences and implications*

Due to the high impact of *shortages,* when they occur, on simulation outputs (Section 3.2), we look at their frequency of occurrence and at their impact on the results (Figure 4). Overall, simulations with shortages are less frequent than simulations without (less than 14% of the simulations). In the recovery case, shortages are almost absent (less than 1.4% of the simulations)[7].

Conversely, simulations considering rebuilding demand show a higher incidence of shortages (22% of the simulations) and outlier results are all associated with this case.

The occurrence and extent of shortages is particularly pronounced when a combination of factors is present: a ψ value above 0.8, a short rebuilding time (e.g. three or six months), and (to a lesser extent) a slower pace of overproduction. Moreover, slight differences in parameter sets fulfilling this combination of factors lead to higher relative deviations in the results than for the rest of the parameter sets which explains the higher sensitivity of ARIO when assumptions are pessimistic (Section 5.2.1).

Among the different MRIOTs, EXIOBASE 3 demonstrates greater "resilience" to shortages. Very few simulations within this framework exhibit shortages, and there are no outlier results associated with this MRIOT. In contrast, the EORA26 and EUREGIO MRIOTs exhibit a higher susceptibility to shortages.

5.4. *Influence of the parameters on results*

In this section, we describe the most noticeable effects of each parameter on results. See Appendix B for the related figures.

[7]Note that some shortages appear when looking at the sectoral level, but have negligible influence on the aggregated results.

Parameter ψ does not influence the results significantly in the recovery case. This is expected since there are almost no shortages in this scenario. When rebuilding demand is considered, small change to the value of ψ when it is initialy low has marginal if no impact on the results, whereas it can considerably change the results when its value is high. Specifically, when ψ is strictly below 0.90, the results range between -60% and +50% of the direct damages, while a ψ value of 0.90 extends the range to -300% and +50%.

The parameter α_{tau}, which denotes the pace of overproduction, also has limited influence in the recovery case. Lower values of α_{tau}, indicating faster overproduction, expectedly lead to lower maximum losses, ranging from -50% of the direct damages for $\alpha_{tau} = 530$ to -30% for $\alpha_{tau} = 90$. In the rebuilding case, α_{tau} has little effect on the spread of results but shifts them towards gains as its value decreases. For example, gains do not exceed +10% of the direct damages for $\alpha_{tau} = 530$, but increase up to +35% for $\alpha_{tau} = 90$.

The duration of the recovery/rebuilding time plays a key role. In the recovery case, faster recovery times result in lower maximum losses, ranging from -50% of the direct damages for a two-year recovery time to -20% for a three-month recovery time. We found the shape of the recovery curve to have very limited influence on the results. In the rebuilding case, the effect varies depending on the MRIOT considered. For EXIOBASE 3, shorter rebuilding times shift the results towards gains, with the range changing from -50% to +20% for the two-year scenario to -5% to +35% for the three-month scenario. Similar shifts towards gains can be observed for EORA26 and EUREGIO, but as the rebuilding time decreases, the spread of results increases, particularly for EORA26.

We also look at the results of simulations restricted to the historical parameter values found in Hallegatte (2013) for ψ (0.8) and α_τ (365 days). The range of results for this restricted set falls between -62% and +2% of the direct losses (Figure B.6). The difference in results spread when considering or not rebuilding demand remains when restricting the parameters to these values: with rebuilding demand, results are in the -62% to +2% range, where without rebuilding demand, they are within -15% to -45%. However, all average results are similar with and without rebuilding demand: between -25% and -30% of the direct losses, with the notable exception of simulation using EUREGIO MRIOT and considering rebuilding demand, where the average result is -40%.

5.5. *Impact on other regions*

We also examine the indirect impacts in other regions to account for cross-border impacts. When not considering a rebuilding demand, we find that most simulations result in production gains, although these gains do not exceed +3% of the direct damages[8]. In rare instances where indirect impacts result in losses, they represent less than -0.5% of the direct damages.

In simulations with rebuilding demand, most outcomes are also gains, and in this case tend to be significantly higher than in the recovery case. For instance, these gains (aggregated over all sectors) reach up to +0.03% of yearly production in France (5% of the initial direct damages), +0.01% of yearly production in the Rest Of the World (ROW) region (+25% of the initial damages), +0.020% in China (+10% of the initial damages) and +0.002% of yearly production in USA (+2% of the initial damages). Several simulations which result in significant losses. For instance

[8]Such gains are explained by shifts in trade relations across regions following the shock

in the ROW region, more than 10 simulations lead to losses higher than -50% of the direct losses. Note here, that ROW region aggregates the losses of a large number of regions. When comparing to the actual size of the ROW economy, the highest indirect damages represent less than -0.2% of yearly production. For France, highest indirect impacts are less than -0.3% of yearly production.

Next we look at the variation of results across the different MRIOTs. Contrary to Germany, there is a higher variability of results between MRIOTs when not considering rebuilding demand. For instance, simulation with EORA26 lead to gains in China that are ten times higher in average than with EUREGIO or EXIOBASE 3. Noticeably, simulations with EUREGIO show slightly higher gains in France and slightly lower gains in USA and ROW compared to EORA26 and EXIOBASE 3. When considering rebuilding demand, results spread is lowest for EXIOBASE 3 and highest for EORA26 when considering rebuilding demand in all regions, similar to Germany.

It is worth noting, that when using the EXIOBASE3 MRIOT, losses are not observed in the rebuilding case except for very rare cases in USA.

At the sector-level, the majority of the gains are driven by the "Manufacturing" sector (Which also answers the rebuilding demand when it exists and is subject to more interregional trade relations than the "Construction" sector). On the other hand, no significant patterns emerge in terms of losses, except that the "Construction" and "Other" sectors exhibit noticeably fewer losses compared to the rest of the sectors. Figures for these results are presented in Appendix B.1.

6. Conclusions

In this paper we carry out an in-depth sensitivity analysis of ARIO, a model which has often been used in the literature to assess the indirect economic impact of disasters, and whose mechanisms have been used as a foundation by numerous other models (Colon et al., 2019; Koks and Thissen, 2016; Otto et al., 2017; Shughrue and Seto, 2018). We find that the choice of taking into account or not the demand for reconstruction after a disaster especially leads to large differences in the results.

When taking into account this demand, i.e. if we suppose that the recovery can only happen via some economic sectors producing more to rebuild what was destroyed by the disaster, the economic impact of the disaster can be positive (i.e. economic gains). The extra demand can indeed act as a stimulus for the economy (Hallegatte, 2013). It can also be largely negative, as the extra demand may conversely create shortages harming the whole economy.

When we do not take into account this demand, i.e. if we suppose that the recovery occurs exogenously without any demand to rebuild damaged infrastructures, then the economic impact is always moderately negative. In our simulations, when taking into account rebuilding demand, total production change ranges from about +40% (i.e. gains) to -250% (i.e. losses) of the direct losses. When we do not take into account this demand, total production change ranges only from -50% to -10% of the direct losses.

Both hypotheses can be found in the literature, in different papers (e.g., Wang et al. (2020) and Koks et al. (2014)). Both choices represent extreme cases, as it may be expected that reconstruction will lead to at least some demand to the "Construction" sector (see for instance the empirical work by Hsiang (2010)). It may also be expected that the need for rebuilding may not be strictly equivalent to the direct damages, as some destroyed elements may not be reconstructed or new types of infrastructures may be built instead. Our results highlight that a better description of rebuilding may be essential to improve the reliability of natural disaster economic costs models. We can note, however, that some disasters, which lead to business interruptions while not destroying capital, may be studied with models such as ARIO without having to solve this issue. They indeed lead to a zero rebuilding demand. This can be for instance the case of heatwaves, droughts, or power blackouts.

We can also note that, when we do not take into account rebuilding demand, the shape of the exogenous recovery over time only influence the results marginally. When not taking this demand into account, the specificity of the shape of the recovery appears to be only a secondary concern.

When taking into account the rebuilding demand, the economic data used as input to the model appears to play an important role in the simulation results. Using EXIOBASE 3 as the input-output table leads to indirect impacts lower in average than using EUREGIO and EORA26. EUREGIO and EORA26 also show more variability in the results, tied with the presence of important negative outcomes. It is difficult to determine a priori which database is more suited to the economic analysis of a disaster, and, here again, different choices have been made in different papers in the literature. Our results highlight the importance of employing and comparing the outcomes of multiple IO tables in such studies.

Finally, changes in parameters values also have more influence on the results when rebuilding demand is taken into account. Simulations show high sensitivity to parameter ψ and rebuilding duration in this case. Rebuilding durations that are too short especially lead to large indirect impacts : as rebuilding demand per step is high in this case, intermediate demand becomes more rationed which quickly results in shortages. High ψ values are also associated with important shortages and indirect impacts as such values effectively reduce the buffering effect of inventories. We found that values higher than 0.97 lead some results to exceed 500% of the direct damages when rebuilding demand is considered.

These elements show that results are heavily dependent on assumptions about rebuilding and the rigidity of constraints on the actors represented by the values of the parameters. We observe that the ARIO model can both lead to negative and positive impacts (the “creative destruction” hypothesis) which aligns with existing studies. While this provides versatility in representing economic dynamics, it highlights the importance of carefully exploring the range of possible outcomes and avoid limiting studies to one set of parameters values, scenario and IO table or MRIOT. In particular, we suggest that the ARIO model is best used when examining different recovery story-lines from a shock. For instance, comparing results obtained assuming an “optimal recovery path” or a “struggling recovery path” could offer valuable insights at local and global levels, providing both optimistic and pessimistic estimates of aggregated losses from extreme events.

Our analysis did not include parameters related to inventories, such as size and resupply time and sectoral (or even regional) heterogeneity, due to the complexity it would introduce, especially on a per-sector and per-MRIOT basis. Future studies could focus on this aspect to account for dissimilarities across different sectors or regions, especially on inventories management. Further research steps could also involve analyzing the effects of other events using our methodology and conducting an inter-comparison with other models to enhance the robustness and consistency of our findings. Recent events such as the COVID19 pandemic and the war in Ukraine also show how trade relations can changes quickly and how supply chains are put in difficulty (Guenette et al., 2022; Maital and Barzani, 2020). This raise the importance of looking at deeper changes in MRIOTs and how it can influence vulnerability to indirect economics impacts. This paper and the BoARIO package, both provide a starting point toward such studies.

7. Reproducibility and code availability

7.1. BoARIO python package

Our implementation of the ARIO model is available as a python package named `boario`, which can be installed via the Python Package Index (`pip install boario`). The version used in this paper is `boario 0.5.0a0`. Installation instructions, tutorials and examples of use, as well as an extensive documentation of both the model and API is available online at `https://spjuhel.github.io/BoARIO/` and code sources is available on a github repository at `https://github.com/spjuhel/BoARIO`.

7.2. Simulation pipeline

To streamline the management of our simulations, we used Snakemake: a workflow management system that enables the creation and execution of data analysis pipelines (Köster and Rahmann, 2012).

We defined a pipeline that automates the execution of our experiments. This pipeline, hosted on a GitHub repository (`https://github.com/spjuhel/BoARIO-Sensitivity`), provides a comprehensive framework for reproducing all our results effortlessly, albeit with the requirement of access to sufficient computational resources. One of the notable advantages of this approach is the flexibility it offers, as researchers may modify or extend the pipeline to conduct additional experiments using BoARIO, thereby facilitating further investigations.

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Appendix A. BoARIO in depth presentation

Appendix A.1. Model description

Appendix A.1.1. Background and overview

Adaptive Regional Input-Output (ARIO) is an I-O model, designed to compute indirect costs from exogenous shocks. Its first version dates back to 2008 and has originally been developed to assess the indirect costs of natural disasters (Hallegatte, 2008). In this paper we present BoARIO, a generic[9] python implementation, similar to the one described by Hallegatte (2013) with some additions (e.g. inspired by Guan et al. (2020)).

The economy is modelled as a set of economic sectors and a set of regions. In the following, we call an industry a specific (sector, region) couple. Each economic sector produces its generic product and draws inputs from an inventory. Each industry answers to a total demand consisting of a final demand (household consumption, public spending and private investments) coming from all regions (i.e. both local demand and exports), intermediate demand (inventory resupply). An initial equilibrium state of the economy is built based on multi-regional input-output tables (MRIOT). Apart from parameters specific to the MRIOT region-sector typology, BoARIO handles any MRIOT in the same manner.

Multiple kinds of shocks can be implemented:

- On the production capacity directly (one or multiple industries are arbitrarily forced to produce less)
- On the productive capital (one or multiple industries arbitrarily lose some part of their factors of production and are thus forced to both produce less and to build back their capital stock).
- On the households (households of affected regions lose some part of their goods and seek to get them back).

The model then describes how exogenous shocks propagates across the economy at each time step (a day in the present study[10]): the imbalance between production and demand is resolved by a proportional rationing scheme, which then leads some industries and households to not receive the totality of their orders. Industries can buffer these unfilled orders with their "inventories" of input and increase or shift their resupply demand. Currently, households simply register the loss as final consumption not met and do not postpone their demand. During the simulation, industries adjust their production and orders based on both demand and their inventories.

Direct economic impact consists in the valuation of the initial exogenous shock, while total economic impact includes also indirect costs consequent to the propagation. Total economic impact can be measured in two ways:

- Final demand not met, i.e. goods that households could not buy due to rationing.
- Relative production change, i.e. diminished or increased production of industries relative to their initial production.

In this study we focus on the second measure.

[9]In the sense that it is not specifically designed for this study.
[10]Our implementation actually allows for any time granularity.

Appendix A.1.2. Detailed description

Initial state. The initial state refers to an economic equilibrium before any exogenous shocks. Initial values for intermediate orders $O(t=0)$, final consumption $Y(t=0)$ and production $x(t=0)$ are derived from the MRIOT. Inventories $\Omega(t)$ are stocks of inputs an industry can draw into (see below for a detailed description of inventories) and $\Omega(t=0)$ are initialized using the initial intermediate orders: by default, it is assumed that every industry has a certain amount n_{input} of days of inputs ahead in their stocks.

Inventories. In ARIO, economic sectors do not use inputs from other sectors directly, but draw inputs from inventories, that can then be re-supplied with intermediate orders $O(t)$. An industry's inventory is a vector that specifies how much of each product this industry has in stock. Each sector needs intermediate inputs in proportions given by the MRIOT at the initial state. Industries draw inputs from their inventories to try to produce at the optimal production level $x^{\text{Opt}}(t)$. However, these inventories cannot be emptied: actual production $x^{\text{a}}(t)$ can thus be set lower than optimal production $x^{\text{Opt}}(t)$ to be sure that inventories are above a certain threshold (see Production for more details). Inventories have been implemented into ARIO to give a more realistic account of supply chain shocks, which can be mitigated by input stocks. The current state of an inventory for a definite input is expressed as the number of time steps a sector can produce with said input at current production level.

Direct shocks. Direct shocks are exogenous and can occur at any time step t. Conceptually, these shocks are the direct economic consequences of the events we are modelling. They can either be (i) direct production capacity losses or (ii) capital destruction. Capital is the only factor of production, so that in any industry $x\%$ capital destruction turns into $x\%$ production loss, as long as capital is not restored. There are two ways to model capital rebuilding:

Recovery Productive capital recovers from a purely exogenous function and at no cost for the economic agents: capital stock in a directly impacted industry goes back to its original level over time, following a chosen recovery curve, without any need for production sparing for rebuilding. This scenario can model the situation where capital is not actually destroyed but less available for instance.

Rebuilding Productive capital is recovered through an endogenous rebuilding demand $\Gamma(t)$ which consists of new orders directed to sectors that usually provide capital stock: construction, transport equipment, manufacturing, etc. This additional demand leads to a reduction of actual production being allocated[11] to final demand $Y(t)$ or intermediate orders $O(t)$

Production. The production module computes actual production $x^{\text{a}}(t)$ for each industry at the current time step with the following process:

- It computes production capacity $x^{\text{Cap}}(t)$, which is production in the initial state $x(t=0)$ less production capacity reduction.

[11] Such a reduction also happens in the Recovery case but to a lesser extent, as it only comes from the production reduction caused by the event

- It defines optimal production $x^{\text{Opt}}(t)$ as the minimum between production capacity $x^{\text{Cap}}(t)$ and total demand $O(t)+Y(t)+\Gamma(t)$: the model is demand-driven, and industries cannot produce more than total demand.

- Finally, the actual production $x^{\text{a}}(t)$ is computed from $x^{\text{Opt}}(t)$, taking into account inventories constraints. More precisely, an industry can produce $x^{\text{a}}(t)$ only if it has more than a fraction ψ of the required inputs of each type to produce $x^{\text{a}}(t)$ for n_{input} time steps in a row, in order to model producers' or cautious anticipatory behavior. In order to satisfy this constraint, if the inventory for an input is $x\%$ below the aforementioned threshold, actual production $x^{\text{a}}(t)$ is reduced by $x\%$ compared to optimal production $x^{\text{Opt}}(t)$. This constraint must be satisfied for each type of input (i.e. sectors) involved.

- Lastly, inputs required for production are then drawn from their respective inventories.

Orders and demand. The order/demand module computes the various demands. Total demand consists of final demand $Y(t)$, intermediate orders $O(t)$ and rebuilding demand $\Gamma(t)$.

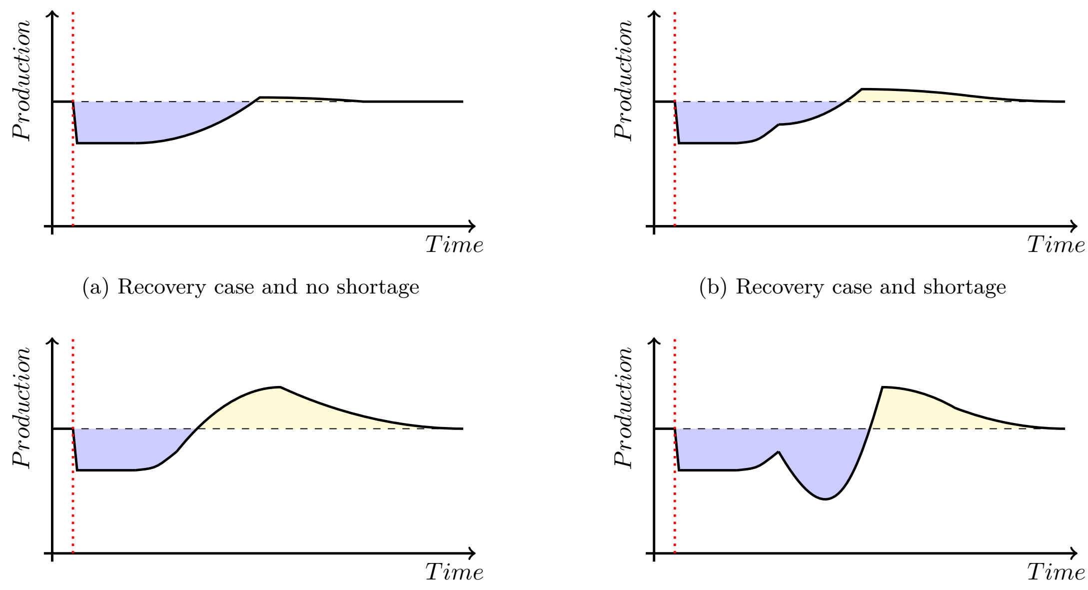
- Final demand $Y(t)$ for each region is exogenous and set by the MRIOT. Currently, it stays fixed during the simulation.

- Intermediate orders $O(t)$ are decided based on inventories and consists of two parts: the first part is the amount of inputs used to produce during the current step, while the second is a fraction $\frac{1}{\tau_{\text{inv}}}$ of the remaining gap with inventory goal. Inventory goals are defined as the inventories needed to produce at $x^{\text{Opt}}(t)$.

- In case capital rebuilding has been set as endogenous, only a fraction $\frac{1}{\tau_{\text{rebuild}}}$ of the remaining rebuilding demand is ordered at each step, so that rebuilding is not instantaneous but takes a characteristic time τ_{rebuild}. Rebuilding demand is used to build back capital stocks and thus restores production capacities to their pre-shock levels. If capital rebuilding is exogenous, there is no rebuilding demand.

Distribution. The distribution module allocates the actual production towards the various demands. Distribution follows a proportional rationing scheme: if total demand cannot be met, intermediate orders $O(t)$, final demand $Y(t)$ and rebuilding demand $\Gamma(t)$ receive actual production according to their share of total demand.

Overproduction. In ARIO, industries can temporarily increase their production capacity from $x^{\text{Cap}}(t)$ to $\alpha \times x^{\text{Cap}}(t)$ when they cannot meet total demand. It is a gradual process: when needed, the overproduction factor α can switch from a base value α^{b} (most often 1) up to $\alpha^{\max}$ with an exogenous characteristic time τ_{α}. The evolution of also depends on a scarcity index, defined as unmet demand divided by total demand: it is faster the higher the scarcity index is. In the current state of development of BoARIO, overproduction comes at no cost for the economic agents: it is limited by the fact that it is not an instantaneous process and that it cannot exceed $\alpha^{\max}$.



(a) Recovery case and no shortage

(b) Recovery case and shortage

(c) Rebuilding case and no shortage

(d) Rebuilding case and shortage

Figure A.5: Basic ARIO responses.

Coping behavior. In addition to overproduction, industries can change their suppliers to some extent, which introduces more substitutability in ARIO than in a "pure" IO model. As shortages start to appear, demand is still distributed among suppliers in the same proportions as before the shock. However, as unmet demand grows, suppliers that have not been affected by direct impacts (on capital or production) can overproduce and catch demand from new buyers. Buyers will then marginally shift their orders to producers that can overproduce. This feature draws on (Guan et al., 2020).

Appendix A.2. Qualitative behavior

In order to present a general overview of the ARIO model, we describe here four elementary responses an industry can have following a shock, depending on the rebuilding demand and the parameters.

a) When the industry does not have to answer a rebuilding demand, or in the recovery case, and no shortage happens (either because the shock is too small or the parameters not too constraining). The model suffers a loss of production for the duration of the event and then slowly regains its production output via the recovery as well as the overproduction mechanism. A small overshoot to refill possible remaining gaps in inventories can be seen before initial equilibrium is found again.
b) If a shortage happens, it slows down the return of production level to its initial amount, possibly extending the recovery period. It may also slightly increase the overshoot in production as inventory gaps are increased by the longer recovery.

c) When the industry answers a rebuilding demand, but no shortage happens, production rises more sharply due to the increased scarcity created by the rebuilding demand. Production also continues to increase as long as total demand is not met, and starts decreasing when it is met and remaining rebuilding demand and inventory gaps are answered.

d) If a shortage happens, production reduces to match its inventories. As long as total demand remains higher than production for the input(s) responsible for the shortage, the inventory gap continues to increase and production to decrease. This stops when production is low enough and received orders are high enough so that the gap starts decreasing. Production then increases back as in the last phase of c), but sharply due to the increased orders to refill inventories.

Actual responses can of course be more complex, as interrelations between industries create feedbacks. As such, shortages can occur earlier or later, at several different times, and decrease production to a greater extent.

Appendix A.3. Hypotheses, limitation, and specifics

Building agent-based models such as ARIO requires a trade-off between the simplicity of the mechanisms described and the amount of parameters to calibrate, and therefore the transparency of modeled impacts. Considering both the conceptual model or its implementation, several hypotheses are made, leading to important limits.

Appendix A.3.1. Hypotheses

- Production is Leontief-based: no substitution possible between different inputs
- Goods produced in the same sector but in different locations are perfect substitutes.
- Industries can always hire (for overproduction).
- Industries and households can always buy goods (no prices, no wages, no budget).

Appendix A.3.2. Limitations

- There are multiple parameters, which are difficult to calibrate, notably because of a lack of empirical data (inventory size, characteristic times, . . .).
- The model does not account for price variations.
- The implementation does (yet) not account for the role of labor (notably the reduction in production capacity due to workers not being able to work during the event).

Appendix B. Detailed results

Appendix B.1. Results for historical parameters values

Figure B.6 shows the results of simulations restricted to historical parameter values found in the article by Hallegatte (2013): $\psi = 0.8$ and $\alpha_\tau = 365$.

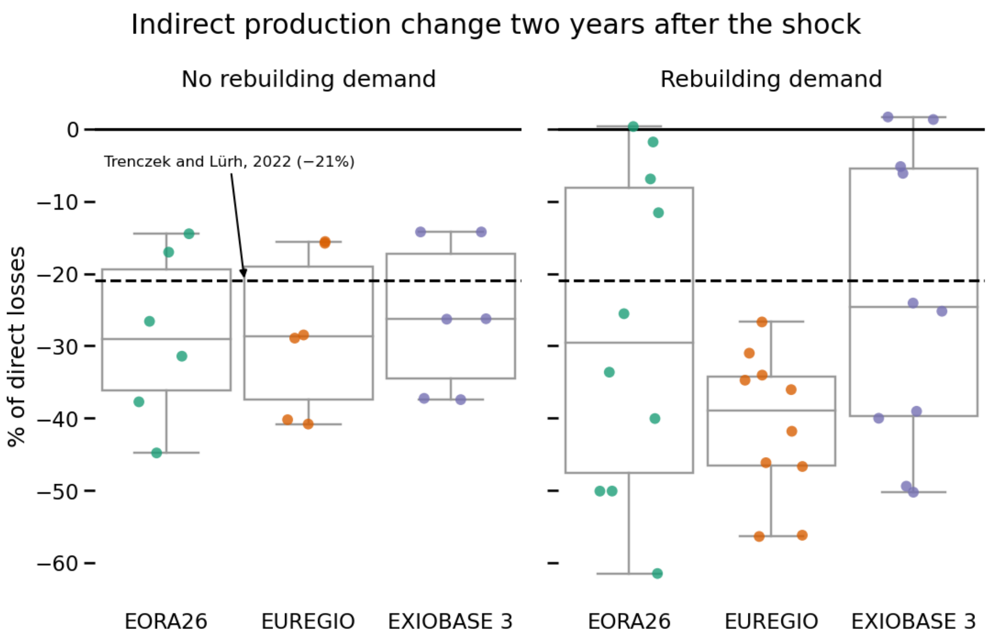


Figure B.6: Results obtained when setting $\psi = 0.8$ and $\alpha_\tau = 365$.

Appendix B.2. Influence of the different parameters

Figure B.7 differentiate the results of simulations by the recovery or rebuilding length that was used (in days).

Figure B.8 differentiate the results of simulations by the ψ value that was used.

Figure B.9 differentiate the results of simulations by the α_τ value that was used (in days).

Appendix B.3. Impacts on other regions

Figures B.10 to B.17 show the results for some regions not directly affected by the event, both aggregated results over all sectors, and per economic sector results.

Appendix C. MRIOT comparison

Figures C.18 to C.20 show some comparisons of the technical coefficient matrix of the different tables used.

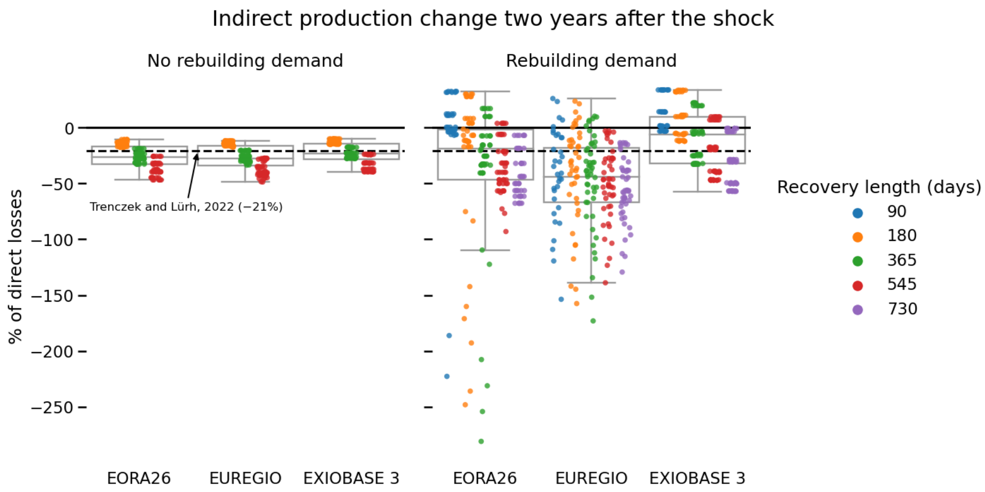


Figure B.7: Influence of rebuilding time on results.

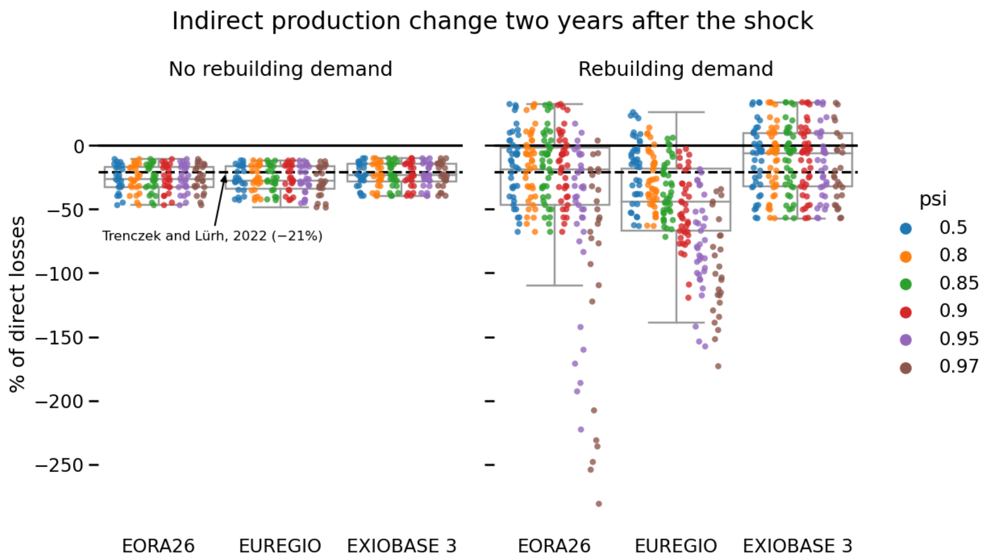


Figure B.8: Influence of ψ on results.

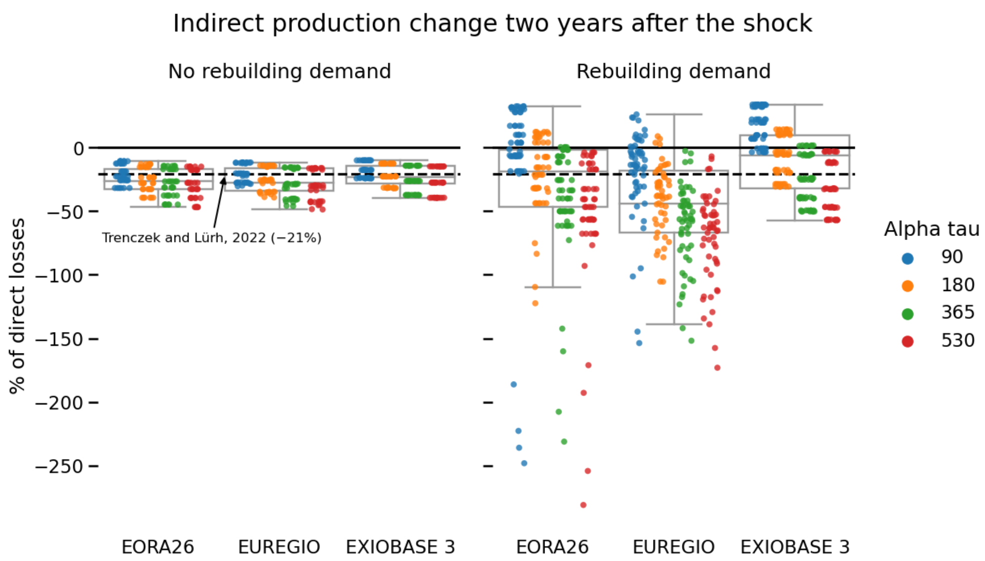


Figure B.9: Influence of α_τ on results.

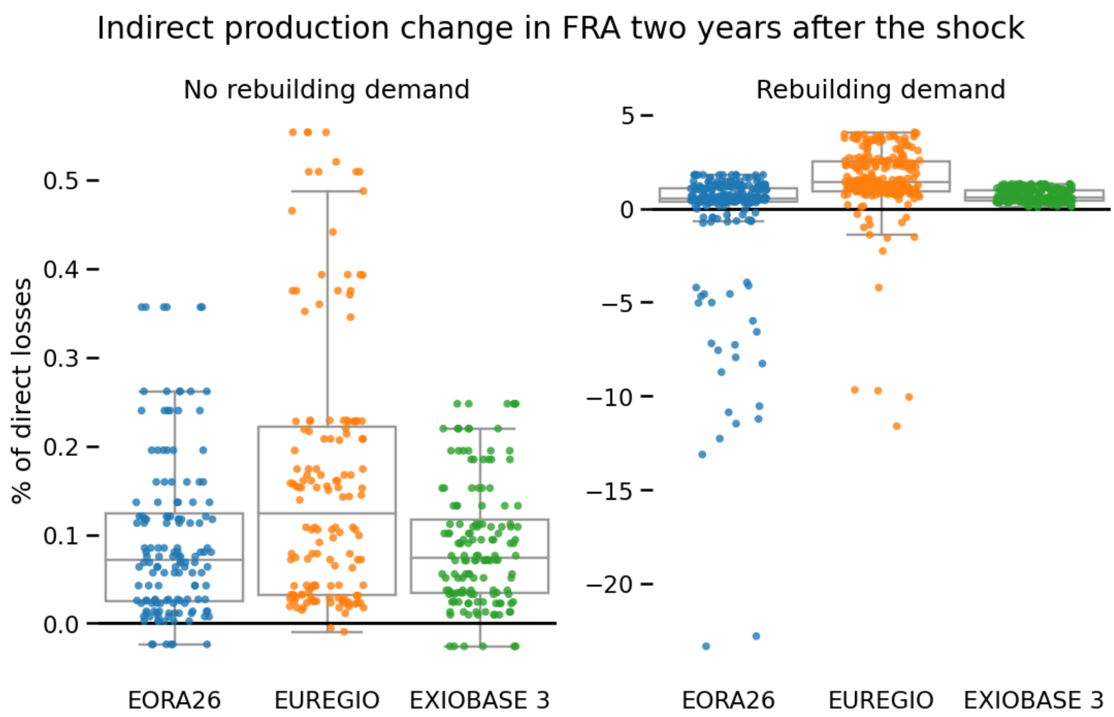


Figure B.10: Results (aggregated) in France.

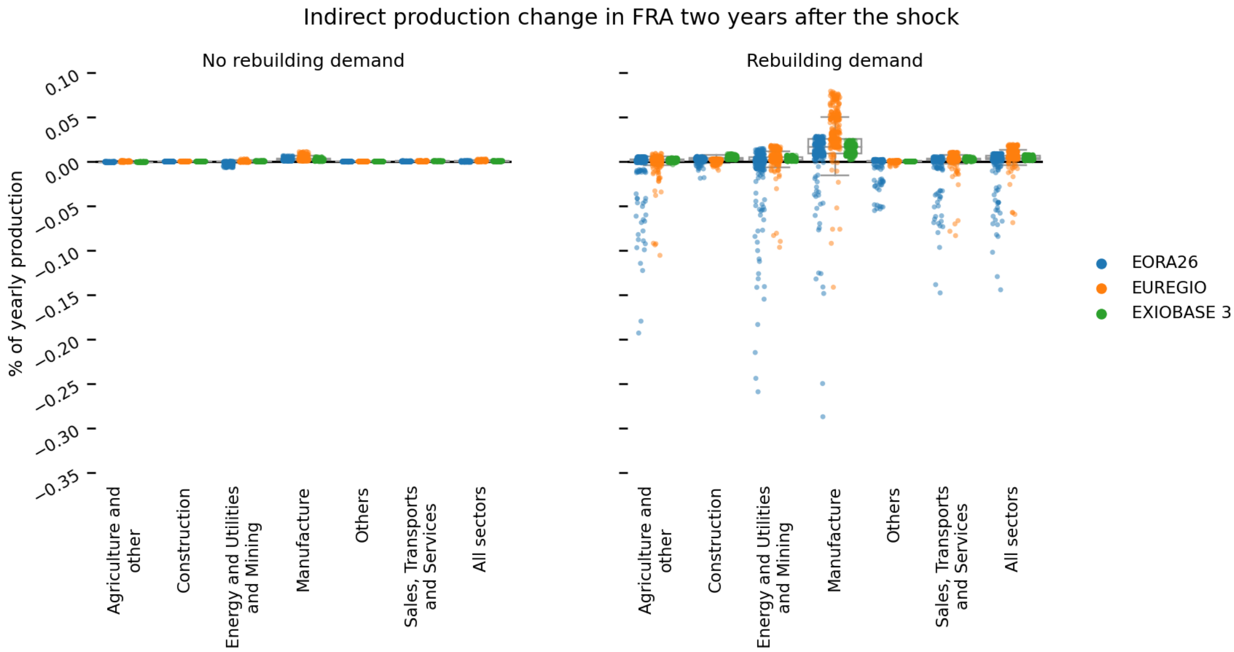


Figure B.11: Results (per sector) in France.

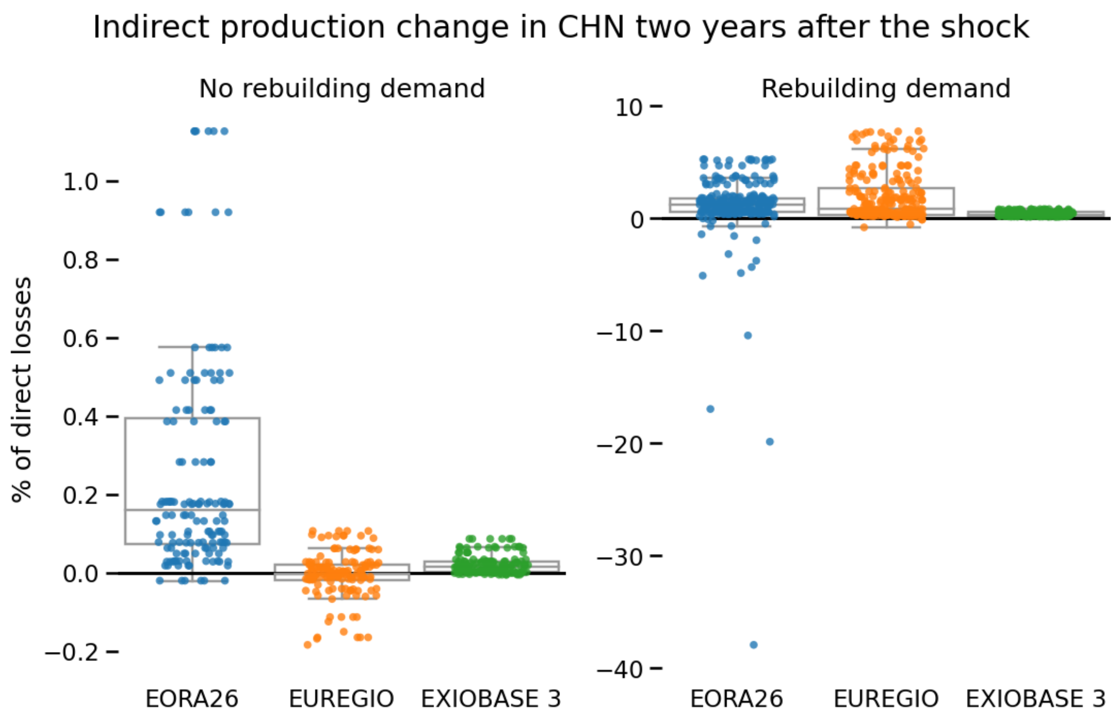


Figure B.12: Results (aggregated) in China.

This paper is a **non-peer reviewed preprint** submitted to EarthArXiv. This paper was submitted to the journal **Risk Analysis**.

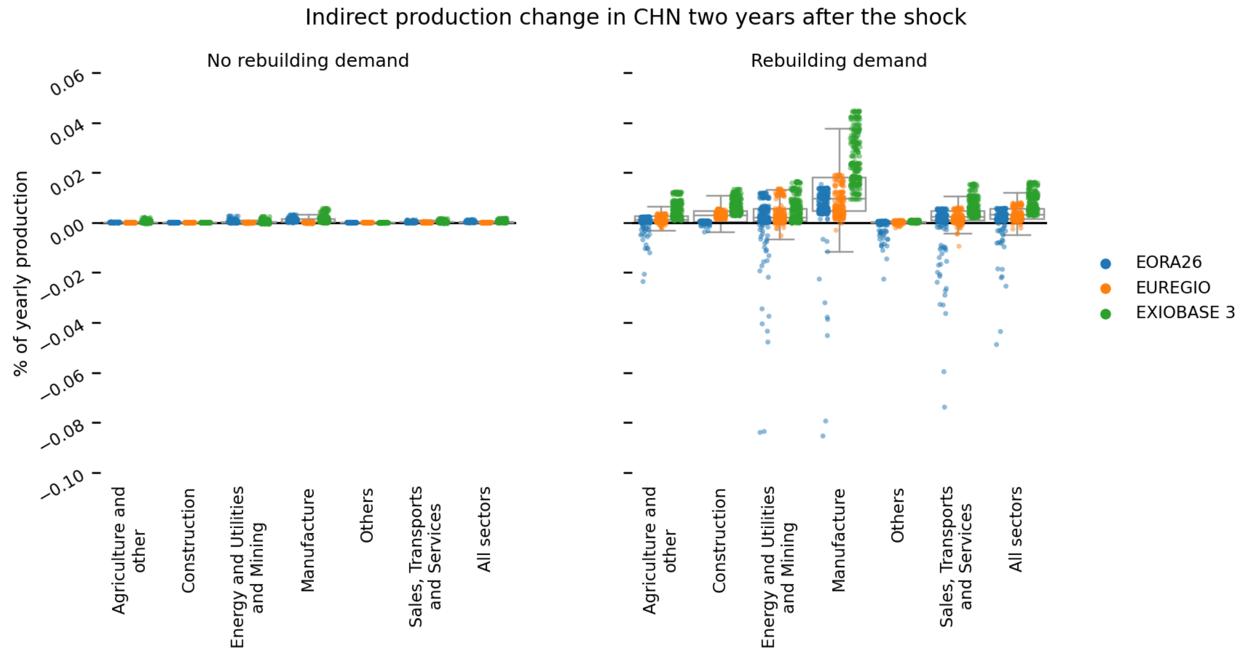


Figure B.13: Results (per sector) in China.

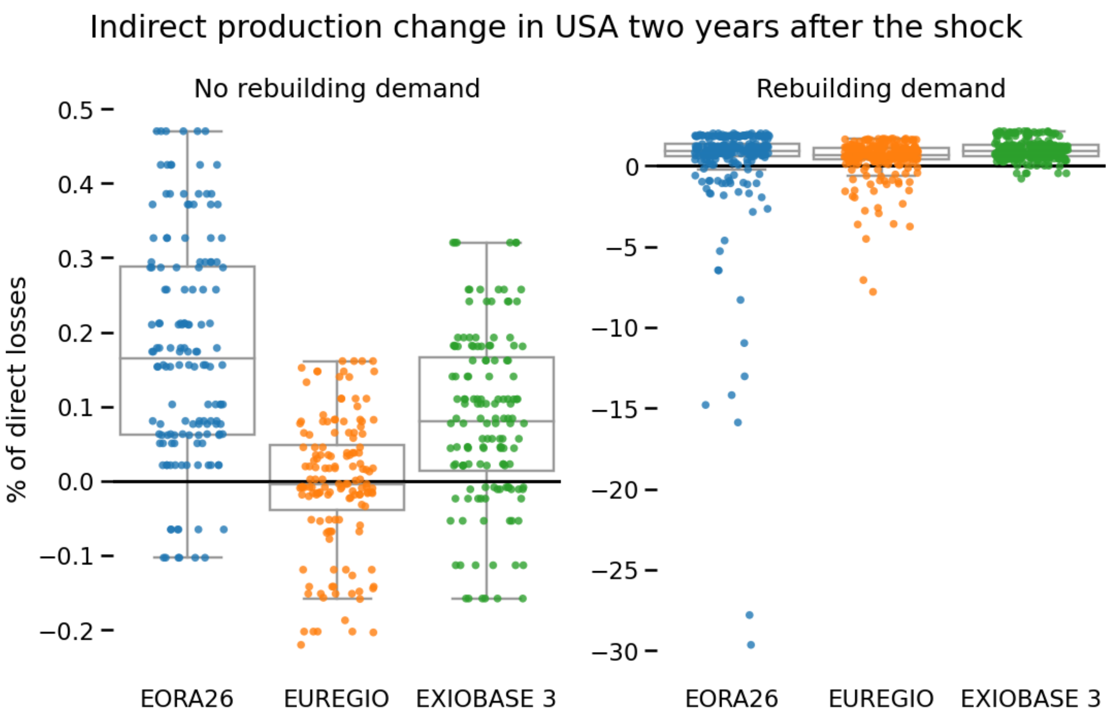


Figure B.14: Results (aggregated) in the United States.

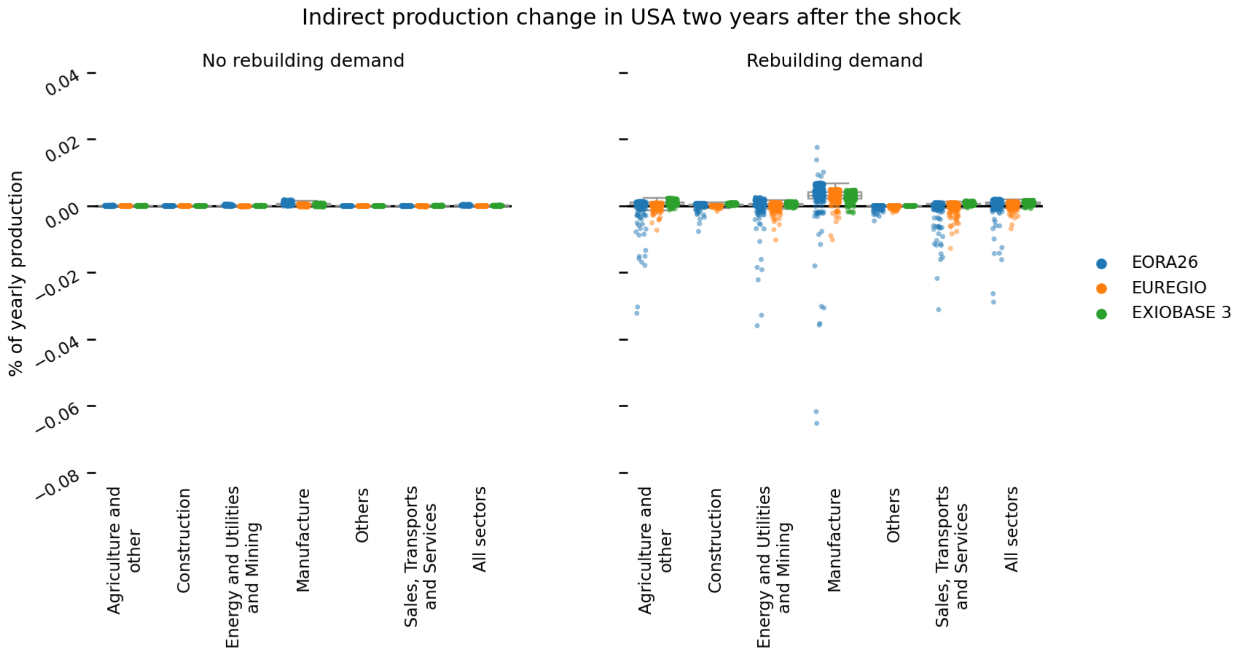


Figure B.15: Results (per sector) in the United States.

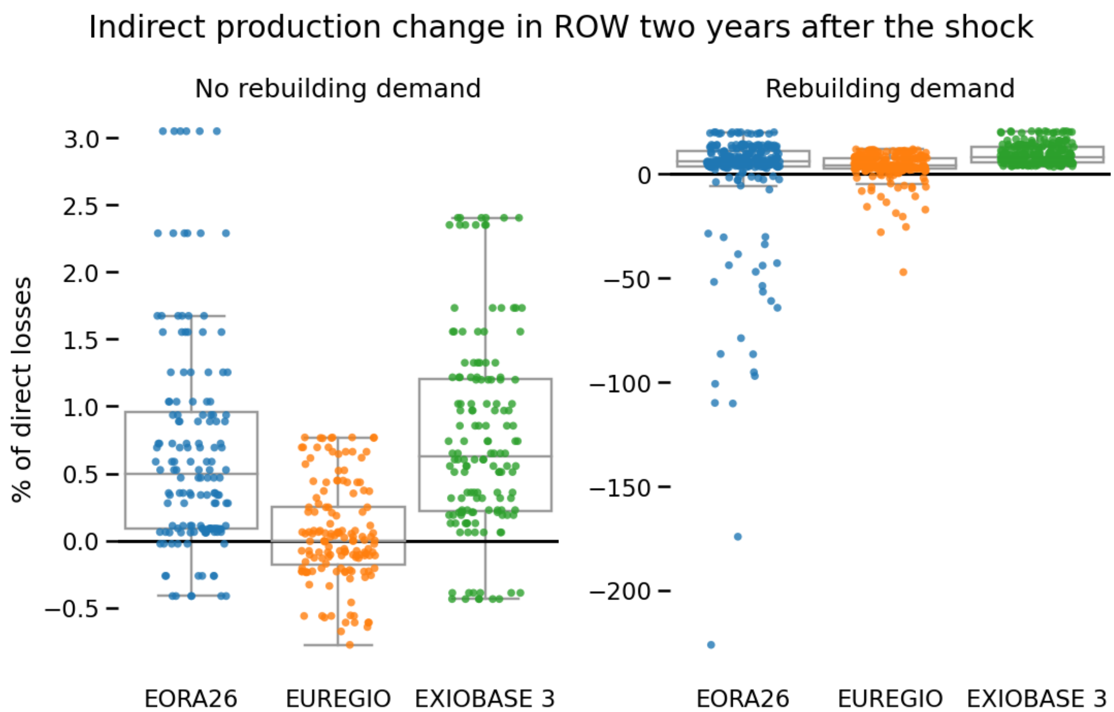


Figure B.16: Results (aggregated) in the rest of the World, i.e. the world without Germany, USA, France and China.

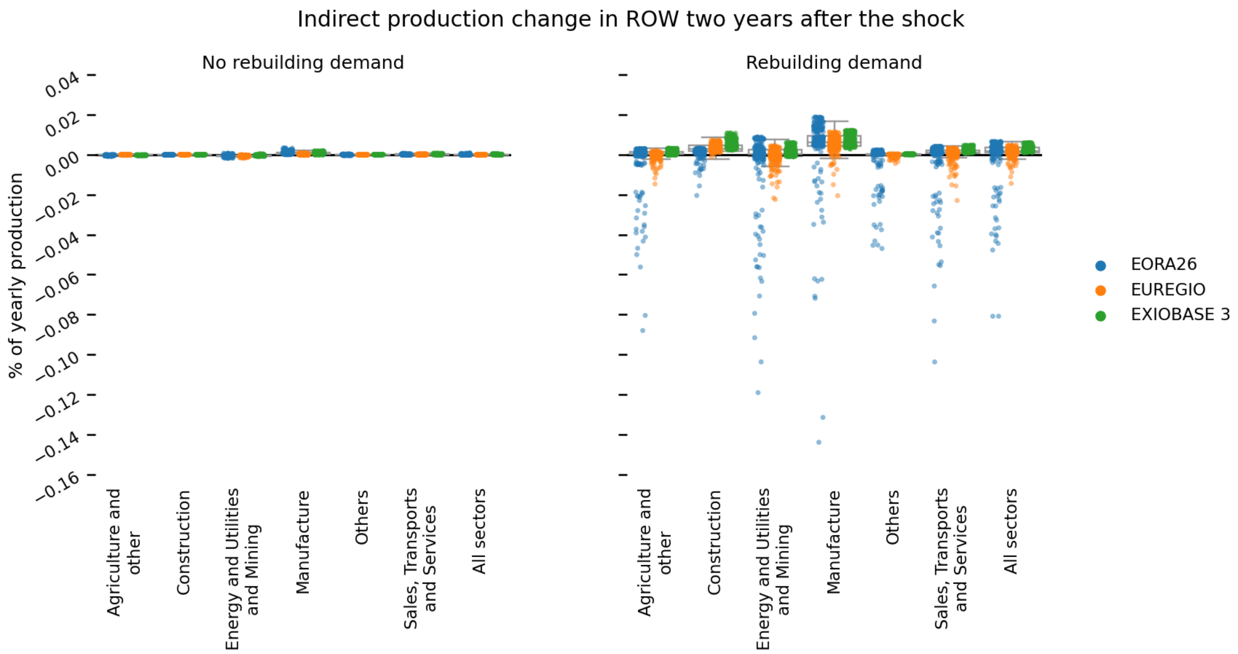


Figure B.17: Results (per sector) in the rest of the World, i.e. the world without Germany, USA, France and China.


Comparing technical coefficients of EORA26 2010 with EXIOBASE3 2010
input region-input sector
output region-output sector
log10 ofabsolute relative difference
CHN-Agriculture and other
CHN-Construction
CHN-Energy and Utilities and Mining
CHN-Manufacture
CHN-Others
CHN-Sales, Transports and Services
DEU-Agriculture and other
DEU-Construction
DEU-Energy and Utilities and Mining
DEU-Manufacture
DEU-Others
DEU-Sales, Transports and Services
FRA-Agriculture and other
FRA-Construction
FRA-Energy and Utilities and Mining
FRA-Manufacture
FRA-Others
FRA-Sales, Transports and Services
ROW-Agriculture and other
ROW-Construction
ROW-Energy and Utilities and Mining
ROW-Manufacture
ROW-Others
ROW-Sales, Transports and Services
USA-Agriculture and other
USA-Construction
USA-Energy and Utilities and Mining
USA-Manufacture
USA-Others
USA-Sales, Transports and Services
3.5
3.0
2.5
2.0
1.5
1.0
0.5

Figure C.18:

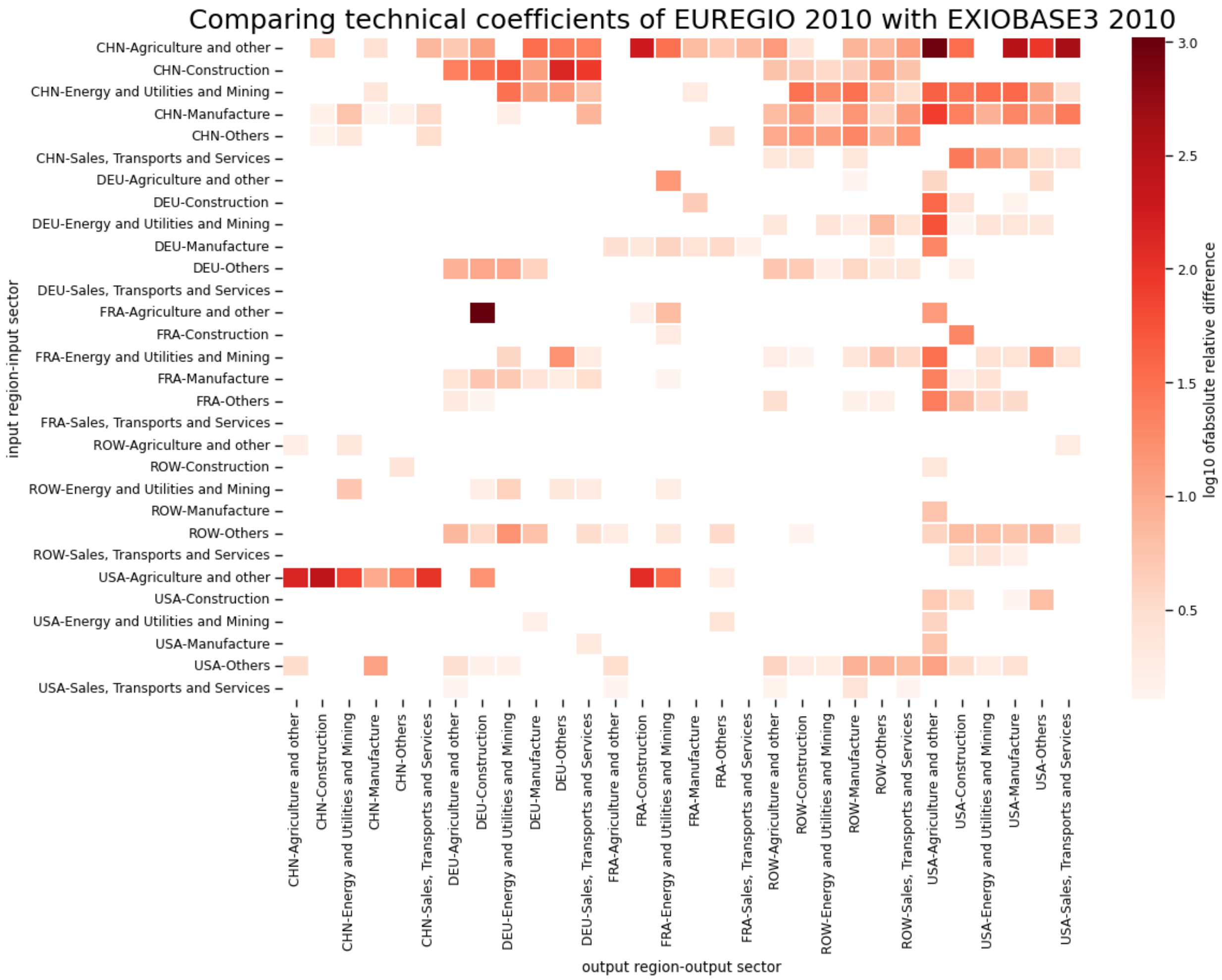

Comparing technical coefficients of EUREGIO 2010 with EXIOBASE3 2010
input region-input sector
output region-output sector
log10 ofabsolute relative difference
CHN-Agriculture and other
CHN-Construction
CHN-Energy and Utilities and Mining
CHN-Manufacture
CHN-Others
CHN-Sales, Transports and Services
DEU-Agriculture and other
DEU-Construction
DEU-Energy and Utilities and Mining
DEU-Manufacture
DEU-Others
DEU-Sales, Transports and Services
FRA-Agriculture and other
FRA-Construction
FRA-Energy and Utilities and Mining
FRA-Manufacture
FRA-Others
FRA-Sales, Transports and Services
ROW-Agriculture and other
ROW-Construction
ROW-Energy and Utilities and Mining
ROW-Manufacture
ROW-Others
ROW-Sales, Transports and Services
USA-Agriculture and other
USA-Construction
USA-Energy and Utilities and Mining
USA-Manufacture
USA-Others
USA-Sales, Transports and Services
3.0
2.5
2.0
1.5
1.0
0.5

Figure C.19:

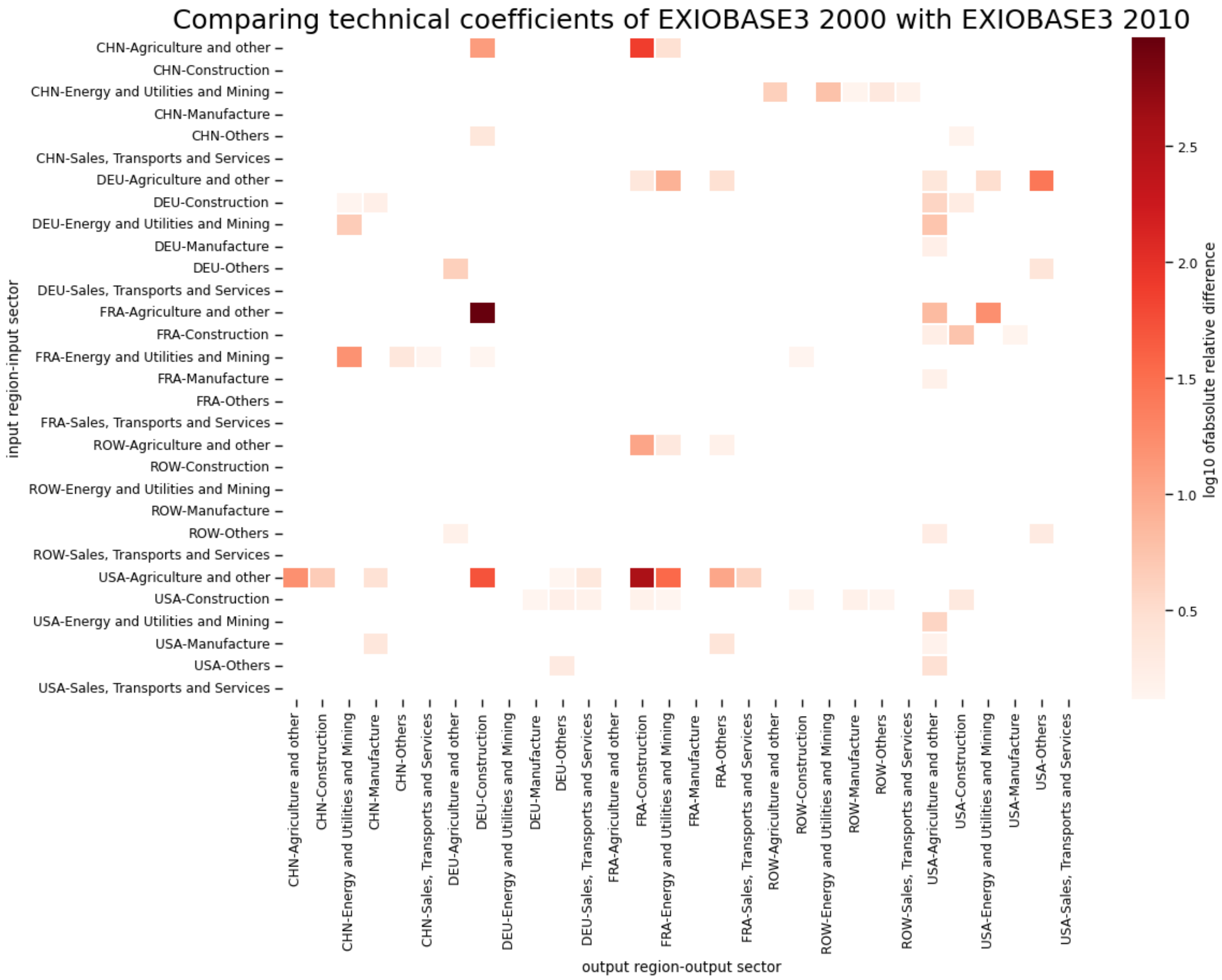

Comparing technical coefficients of EXIOBASE3 2000 with EXIOBASE3 2010
input region-input sector
CHN-Agriculture and other
CHN-Construction
CHN-Energy and Utilities and Mining
CHN-Manufacture
CHN-Others
CHN-Sales, Transports and Services
DEU-Agriculture and other
DEU-Construction
DEU-Energy and Utilities and Mining
DEU-Manufacture
DEU-Others
DEU-Sales, Transports and Services
FRA-Agriculture and other
FRA-Construction
FRA-Energy and Utilities and Mining
FRA-Manufacture
FRA-Others
FRA-Sales, Transports and Services
ROW-Agriculture and other
ROW-Construction
ROW-Energy and Utilities and Mining
ROW-Manufacture
ROW-Others
ROW-Sales, Transports and Services
USA-Agriculture and other
USA-Construction
USA-Energy and Utilities and Mining
USA-Manufacture
USA-Others
USA-Sales, Transports and Services
output region-output sector
log10 ofabsolute relative difference
2.5
2.0
1.5
1.0
0.5

Figure C.20: