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Evaluating the robustness of the ARIO model for a local disaster:
2021 flooding in GermanySamuel Juhel^{1,2,*} , Adrien Delahais¹ and Vincent Viguié¹ ¹ CIRED, Ecole des Ponts, AgroParisTech, EHESS, CIRAD, CNRS, Université Paris-Saclay, Nogent-sur-Marne, France² LMD, Ecole Normale Supérieure, Paris, France

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E-mail: pro@sjuhel.org**Keywords:** ARIO, flooding, indirect impacts, input-output models, natural disasters, reconstructionSupplementary material for this article is available [online](#)**Abstract**

Given the interconnectedness of modern economies and the widespread adoption of just-in-time production methods, even minor disruptions caused by natural disasters can lead to substantial indirect economic impact. A substantial body of literature has explored this phenomenon, using input-output analysis, computable general equilibrium and agent-based models. However, these models (i) heavily rely on parameters and data that often lack empirical grounding or (ii) exhibit considerable uncertainty, making it challenging to assess their reliability. The ARIO model has been widely used in the literature and has provided theoretical foundation for several related models. Using the July 2021 floods in Germany as a case study, we assess the sensitivity of the results of this model by varying key parameters, as well as the multi-regional input-output tables (MRIOTs), which constitute its primary input data. To facilitate this analysis, we introduce a new, resource-efficient Python implementation of the ARIO model, enabling the execution of a large number of simulations. Our findings highlight the substantial impact of data source and parameter selection on model outcomes, especially so when post-disaster rebuilding is costly. To ensure the robustness of their results, future studies on indirect economic impacts should be careful about recovery dynamics, consider multiple scenarios and compare results using MRIOTs from various sources.

1. Introduction

Natural disasters have long been recognized for their significant economic consequences. However, the issue has gained even greater prominence as an increase in the frequency and severity of extreme events is expected in the future due to climate change (Lange *et al* 2020). The interconnectedness of economies and the prevalence of just-in-time production processes has raised alarms about the potential for even minor disruptions in supply chains to have profound indirect economic impacts (Hallegatte 2015, Botzen *et al* 2019). 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.

While empirical studies have provided valuable insights into the global economic costs of natural disasters, accurately assessing these costs remains challenging. Obtaining precise data on economic production for short-term analysis, especially at scales below a year, can be difficult. Such data is often not readily available or may be subject to significant measurement errors. Moreover, disentangling the consequences of a natural disaster from other socio-economic drivers in the data can be intricate (Noth and Rehbein 2019). Finally, natural disasters often trigger a cascade of secondary effects, the full picture of which may not be entirely clear-cut in empirical data (Hallegatte 2015). To address these issues, various modeling approaches have been proposed, including computable general equilibrium (CGE) models (Rose *et al* 2011), input-output analysis (Santos *et al* 2014, Galbusera and Giannopoulos 2018, Zhang *et al* 2018, Zeng *et al* 2019), and agent-based modeling (Otto *et al* 2017, Inoue and Todo 2019, Pichler and Farmer 2021).

These models can be parameterized to use existing empirical assessments of the direct shock caused by a natural disaster, and provide insights into its associated indirect impacts which may not be directly evaluated through empirical means. However, the reliability of the results generated remains uncertain. Previous studies have demonstrated the sensitivity of these models to the choice of parameters (Hallegatte 2008, 2013, Ranger et al 2010, Koks et al 2014).

Another key aspect of modeling indirect economic impacts is the calibration of the economic interactions, which are based on so called Local or Multi-Regional Input-Output tables (LIOT/MRIOT). To our knowledge, no study exists on the sensitivity to the selection of MRIOTs 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, Timmer et al 2015, Stadler et al 2018, Thissen et al 2018).

In this study, we focus on the July 2021 floods in Germany as a case study to conduct an in-depth examination of the sensitivity of the Adaptive Regional Input-Output model (ARIO), which extends an input-output (IO) framework with additional adaptive dynamics (Hallegatte 2008, 2013). This model is one of the most frequently used in the natural disasters economic impact assessment literature (Hallegatte 2008, Ranger et al 2010, Koks et al 2014, Zhang et al 2018, Guan et al 2020, Wang et al 2020), and several other models share its core concepts (Koks and Thissen 2016, Otto et al 2017, Shughrue and Seto 2018, Colon et al 2019).

We explore a set of parameters and input data and compare simulation outcomes with existing evidence of the economic consequences of the event (section 2). Our study brings three original contributions: first we conduct a sensitivity analysis of the ARIO model in a multi-regional framework³. Second we compare different depictions of the post disaster recovery process using scenarios with and without reconstruction effort, third we compare results obtained using different MRIOTs.

For this analysis, we first carry out simulations over a large set of parameters, and then exclude 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 the ARIO model are crucially determined by the modeling of the reconstruction process. Moreover, we identify how the ARIO model can exhibit either linear or non-linear behaviour. A threshold exists for direct impacts, beyond which shortages begin to occur, leading to non-linear indirect impacts that become significantly more pronounced than when no shortage occur. Various parameter choices alter this threshold, resulting in a wide range of outcomes observed from simulations of the same event that differ only in one parameter. This aspect underscores the necessity for more justification and transparency regarding the modeling choices used.

Although the generalisation of our results to other models is not straightforward, the similarities these models share with the ARIO model highlight the uncertainty of the estimates obtained, and particularly on the influence of the hypotheses assumed for reconstruction mechanism, which differ among studies (Willner et al 2018, Koks et al 2019, Shughrue et al 2020).

2. Methods

We study the sensitivity of the ARIO model (see section 2.1) 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 the 2021 floods in Germany (see section 2.4) using 3 different MRIOTs (see section 2.2), and a range of values for the parameters (section 2.3). Section 2.5 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 observations (see section 2.6).

2.1. The ARIO model

We employ the BoARIO python implementation of the ARIO model (Juhel 2024a), which is very similar to the one described in (Hallegatte 2013) with some additions from (Guan et al 2020).

The economy is modelled as a set of economic *sectors* and a set of *regions*. These regions and sectors are entirely defined by the MRIOT used (see section 2.2), thus the model itself is agnostic from any specific typology of regions and sectors. We use the term *industry* to designate a specific couple of a sector and a region, i.e. the basic productive agents.

Each industry produces a unique product which is assumed to be the same for all industries of the same sector. Each industry keeps an inventory of inputs it requires for production. These inventories are expressed

³ Previous sensitivity analysis were conducted but in a mono-regional framework, where the interaction between unaffected regions were not considered (Hallegatte 2008, 2013, Koks et al 2014).

Table 1. MRIOTs used in this study and their specificities.

Name	Number of sectors	Number of regions	Years available	Source
EXIOBASE 3 Stadler <i>et al</i> (2018)	163	49 (44 Countries and 5 RoW regions)	1995-2011 Estimates up to 2022	Zenodo
EUREGIO Thissen <i>et al</i> (2018)	14	264 (254 UE NUTS2 regions, 16 Countries, 1 RoW region)	2000-2010	PBL
EORA26 Lenzen <i>et al</i> (2012)	26	189 Countries	1990-2016 Up to 2022 with subscription	EORA website

for each input as the number of simulation steps⁴ an industry can produce with said input while maintaining its current production level.

Each industry answers a total demand consisting of a share of the final demand (accounting for household consumption, public spending and private investments) of all regions (i.e. both local demand and export) and a share of the intermediate demand (made up of inputs inventory resupply requirement from all industries). The initial equilibrium state for the economy is built based on the MRIOT. The model then describes how a local shock affects the dynamics of each industry for a chosen number of steps. For a detailed description of the model refer to the model documentations⁵.

2.2. Multi-regional input-output tables

MRIOTs are comprehensive economic data sets that capture inter-regional trade flows, production activities, and consumption patterns across different regions or countries. These tables provide a detailed breakdown of the flows of goods and services between industries within each region and between regions themselves. MRIOTs are constructed through a combination of national or regional input-output tables, international trade data, and other relevant economic statistics. By integrating data from multiple regions, MRIOTs enable the analysis of global supply chains, international trade dependencies, and the estimation of economic impacts across regions. However, they also come with limitations, such as data inconsistencies across regions, assumptions about trade patterns and production technologies, and the challenge of ensuring coherence and accuracy in the aggregation of data from various sources.

Although MRIOTs are commonly used to calibrate indirect economic impact models, to our knowledge, no study exist comparing the influence of their choice on model outcomes. Yet, MRIOTs can differ a lot, either from the typology of sectors and regions they use, the integration of different economic statistics and the assumptions made to ensure their coherence.

We use three different MRIOTs sources for this study, namely EXIOBASE 3, EUREGIO and EORA26 (see table 1 for their characteristics). We choose these three MRIOTs for their distinct 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.

MRIOTs are rarely available for the most recent years, and studies often employ tables that may be more than a few years old. Zhang *et al* (2018) for instance employ a 2012 version of the WIOD database (Timmer *et al* 2015) to estimate indirect economic impacts of future climate change on the US economy, and Huang *et al* (2020) use a local Chinese IO table also for year 2012, also in order to estimate future impacts. Similarly, Koks *et al* (2014) employ a 1992 local IO table for Rotterdam in their analysis, but justify its use by the fact that relative industrial shares have remained similar over time.

In addition to comparing different sources of MRIOTs we also compare results for both year 2000 and 2010 (as it represents the largest gap in time common to all three MRIOTs, table 1). Note that such comparisons of MRIOT from the same source but for different years have been conducted in Willner *et al* (2018), Kuhla *et al* (2023) and Wenz and Levermann (2016).

In section 2, we present a comparison of the technical coefficients of these MRIOTs. Technical coefficients can be considered as a normalized representation of the economic structure (Miller and Blair 2009), and depict the interdependence between sectors and regions. Although the different tables represent the same economy, we observe significant differences across them, which supports the need for a comparison.

⁴ One day in this study.

⁵ For a mathematical description refer to <https://github.com/spjuhel/BoARIO-Formalism-Latex>. For the documentation of the python package refer to <https://spjuhel.github.io/BoARIO>.

2.3. Parameters choices

2.3.1. Heterogeneity parameter ψ

Parameter ψ is introduced in Hallegatte (2013) and represents the degree of heterogeneity in how inventory reductions impact production across businesses within a sector.

- If ψ is close to 0, a reduction in sector inventory of inputs is distributed uniformly across the firms within the sector (thus shortages arise only when the inventory is almost depleted, i.e. a large share of suppliers are failing).
- If ψ is close to 1, a reduction in sector inventory of inputs is distributed heterogeneously across the firms within the sector, (thus shortages arise sooner, even when only a limited amount of input is lacking at the sector scope).

Hallegatte (2013) evaluates the ARIO 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. The author notably shows that values of 0.5 and 0.7 do not induce forward propagation of the initial shock⁶: using values of ψ below 0.5, *ceteris paribus*, has no influence on the results.

We also find, through preliminary simulations, that marginal changes in ψ 's value when it is close to 1, cause larger changes in results, thus we concentrate more values toward 1 in our analysis, by investigating the following ψ values: 0.5, 0.8, 0.85, 0.90, 0.95, 0.97 and 1.

Note that $\psi = 1$ is a particular case where any gap in inventory instantly translates into loss of production capacity. As such we only include this value in the broad sensitivity analysis, but exclude it from the comparison of MRIOTs.

2.3.2. Overproduction pace τ^α

This parameter determines how an industry can ramp up its production when total demand is larger than current production level. It is a measure of the time it takes for an industry to respond to the scarcity of goods it produces. 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.

The most common value for this parameter in the recent literature is 365 days (Hallegatte 2013, Koks et al 2014, Guan et al 2020), which implies that it takes approximately one year for the industry to reach maximum overproduction. Previous studies used a value of half a year (Hallegatte 2008, Ranger et al 2010, Wu et al 2011).

We broaden the range of values for this parameter to the following values: 90 days, 180 days, 365 days, and 730 days. We chose this set of values for its intuitive understanding, as 90, 180 and 730 days respectively represent paces that are 4 times faster, 2 times faster and 2 times slower than the most common value in the literature. Values over 730 days were not considered as they substantially increase the required computation and start being outside of the usual temporal scope of the ARIO model.

Furthermore, we also look at $\tau^\alpha = 1$, as one day is a hard limit for the overproduction pace where industries adapt instantaneously. Similar to the case $\psi = 1$, we also exclude this value from the MRIOTs comparison.

2.3.3. Recovery scenarios

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

Exogenous restoration The recovery of destroyed productive capital does not induce any endogenous demand in the model. The destruction acts only as a temporary reduction in production capacity, linearly decreasing over time.

Reconstruction effort The recovery of destroyed productive capital is associated to a rebuilding demand, equal to the direct damages. This assumes that the recovery can only happen via some economic sectors producing more to rebuild the assets destroyed by the disaster⁷.

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

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 can affect the results.

⁶ We also confirmed this in preliminary simulations for this case-study.

⁷ See supplementary materials for details on how this demand is distributed among sectors.



Figure 1. Ahr flood in Kreuzberg, Germany, July 2021. Credit: Martin Seifert. This picture has been obtained by the author(s) from the Wikimedia website, where it is stated to have been released into the public domain. It is included within this article on that basis.

In both cases, we also evaluate the sensitivity to the duration of the recovery process. We consider multiple characteristic periods⁸ ranging from three months to two years.

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 scenarios.

2.4. 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 (figure 1). 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 2022, Munich 2022).

Rhine-Westphalia has the largest economy among the German federal states (by GDP) (Welcome to North Rhine-Westphalia 2024), hosting several notable companies such as: ‘E.ON’ (energy), ‘Deutsche Telekom’ (telecommunications), ‘Deutsche Post World Net’ (logistics), ‘Metro AG’ (food trade), ‘ThyssenKrupp’ (automotive supplier), ‘RWE’ (energy) and ‘Rewe Gruppe’ (trade). Major sectors in Rhineland-Palatinate include the production of chemicals, pharmaceuticals, and auto parts, as well as wine growing, ceramics, glass and leather (Rheinland-Pfalz 2015). Note, that it is difficult to precisely estimate how each of these sectors were affected by the flooding (Trenczek *et al* 2022). Witting (2023) mentions the wine and tourism industry of the Ahr Valley were severely affected.

In this study, we use these figures as input to simulate the indirect economic damages of the floods with the ARIOT model. More precisely, we express the direct damages as a share of the 2021 gross value added (GVA) of Germany or of each affected German federal state (depending on the geographic resolution of the MRIOT we use), and distribute these damages to the sectors of the different MRIOTs, using their

⁸ For the ‘Exogenous restoration’ case, a characteristic period of τ^{Recovery} days means that productive capital is recovered in τ^{Recovery} days. For the ‘Reconstruction effort’ case, it means that $1/\tau^{\text{Recovery}}$ of the remaining rebuilding demand is ordered at each step.

contribution to the affected regions GDP as a proxy (similar to what is done in Trenczek *et al* (2022))⁹. Detailed distribution 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 study (section 3.1).

2.5. Outcomes of the model

We look at the total net production change from baseline (no event) over a two years period as this time-frame corresponds well to the temporal scope of the ARIO model.

To facilitate comparison between the different MRIOTs, which encompass varying sets of regions and sectors (ranging from 163 sectors in EXIOBASE 3 to 14 in EUREGIO), we aggregate the results to a common set of five 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.

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

Not all parameter choices lead to results which seem coherent with the reality. At the same time deciding where the limit of plausibility stands precisely (either for parameter choices or for results) is a uneasy task, especially with abstract parameters such as ψ , and in the absence of quantitative empirical data on indirect impacts.

As our objective is to estimate the reliability of results obtained with the ARIO model using different MRIOTs, we remove sets of parameter values which lead to indirect economic costs that are at odds with observations (such as a sudden collapse of the whole German economy after the floods) or with the literature.

First we assume that indirect impacts were not more than one order of magnitude higher than the direct ones, as we did not found specific evidence in the press or literature.

In parallel, 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. The highest ratio we find is a factor of five, which is consistent with the previous assumption of remaining in a range of one order of magnitude.

Thus, our criterion for considering indirect losses to be unrealistic is that they exceed direct damages by more than a factor of five (Carvalho *et al* 2020)¹⁰. Our objective is then to observe the remaining variability in results when using different MRIOTs. In order to maintain a consistent ensemble of parameters settings for all MRIOTs, we remove a set if results match our criterion for at least one of the MRIOT.

3. Results

Section 3.1.1 presents the parameters sets that are removed in addition to the special cases of $\psi = 1$ and $\tau^\alpha = 1$ (as both represent limit case which are interesting for the evaluation of the model behaviour but not for applied interpretation), when we follow the approach described in section 2.6.

Section 3.1 examines the variations in results for Germany, at the aggregated and sector level with a focus on comparing the different MRIOTs used. Section 3.2 emphasizes on the occurrence of shortages during simulations and section 3.4 studies the specific influence of each parameters.

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.

⁹ 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).

¹⁰ 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.

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

Study	Method	Direct damages estimate	Indirect damage estimate	Ratio indirect/direct
Hallegatte (2008)	ARIO v1 ^a	dollar;107 Billion	dollar;42 Billion	39%
Ranger et al (2010)	ARIO v1	dollar;1500 Million	dollar;425 Million	28%
Hallegatte et al (2010)	ARIO v1	€ 1700 - 14 500 Millions	€ 14 - 2000 Millions	0.8%–13%
Wu et al (2011)	ARIO v1	CNY 749 Billion	CNY 301 Billion	40%
Hallegatte (2013)	ARIO v2	dollar;63 Billion	dollar;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 ^b		
Mendoza-Tinoco et al (2020)	Flood Footprint Assessment model	—	—	150%–500%
Tanoue et al (2020)	CGE	dollar;14.7 Billion	dollar;10.6 Billion	72%
Trenczek et al (2022)	Ghosh IO model	€ 33.4 Billion	€ 7 Billion	21%
Carvalho et al (2020)	CGE	0.1% GDP growth	0.5% GDP growth	500%

^a ARIO v1 designate the version presented in Hallegatte (2008), while ARIO v2 designate the updated version of Hallegatte (2013).

^b We consider the first-order Estimated Annual Output Losses (EAOL) of the study which designate indirect impact of events on the impacted region.

Table 3. Sets of parameters removed after selecting simulations with indirect losses less than 5 times the direct damages (And the cases $\psi = 1$ and $\tau^\alpha = 1$). Any set of parameters corresponding to a row of the table was removed. For instance $\{\psi = 0.97, \tau^{\text{Recovery}} = 730, \tau^\alpha = 90\}$ was not removed (as $\tau^\alpha = 90$), but $\{\psi = 0.97, \tau^{\text{Recovery}} = 730, \tau^\alpha = 730\}$ was removed (from fifth row) and $\{\psi = 0.97, \tau^{\text{Recovery}} = 180, \tau^\alpha = 90\}$ as well (from third row).

Heterogeneity	Recovery time	Overprod. pace	Scenario
$\{\Psi\}$	$\times \{\tau^{\text{Recovery}}\}$	$\times \{\tau^\alpha\}$	$\times \{\text{Exo. Restor., Recon. Effort}\}$
$\{0.9\}$	$\{90\}$	$\{90, 180, 365, 730\}$	$\{\text{Recon. Effort}\}$
$\{0.95\}$	$\{90, 180\}$	$\{90, 180, 365, 730\}$	$\{\text{Recon. Effort}\}$
$\{0.97\}$	$\{90, 180, 365\}$	$\{90, 180, 365, 730\}$	$\{\text{Recon. Effort}\}$
$\{0.97\}$	$\{545\}$	$\{180, 365, 730\}$	$\{\text{Recon. Effort}\}$
$\{0.97\}$	$\{730\}$	$\{730\}$	$\{\text{Recon. Effort}\}$
$\{1\}$	$\{90, 180, 365, 545, 730\}$	$\{1\}$	$\{\text{Exo. Restor., Recon. Effort}\}$

Note that, given that the difference between the two recovery scenarios lies in the presence or absence of a rebuilding demand, we will often use this characteristic as a shorthand to refer to the scenarios instead of explicitly naming them.

3.1. Global sensitivity

3.1.1. Restricting the parameters values

Following our criterion, we exclude about 12% of the initial sets of parameters from our assessment¹¹. The excluded sets of parameters are shown in table 3. We observe that excluded sets correspond to high values of ψ , and short recovery times when $\psi \leq 0.95$.

It is challenging to determine if the excluded parameter settings are inherently implausible. A recovery period shorter than one year for an event of this magnitude appears unlikely and evidence suggests that recovery was not fully completed even two years after the event (Witting 2023).

The question regarding the plausibility of ψ values is more complex, as it is difficult to directly evaluate ψ with concrete data. If ψ is considered representative of the average proportion of firms utilizing just-in-time production processes (and thus the proportion of firms directly impacted by any delivery failure) then values above 0.9 seem improbable.

For the purpose of completeness, we also show results without this restriction in section 1.2.

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.

3.1.2. Aggregated impacts

Figure 2 presents the simulated aggregated production change, for the different MRIOTs used. Total production change ranges from about -393% (i.e. losses) to $+68\%$ (i.e. gains) of the direct impact.

¹¹ Without accounting for $\psi = 1$ and $\tau^\alpha = 1$.

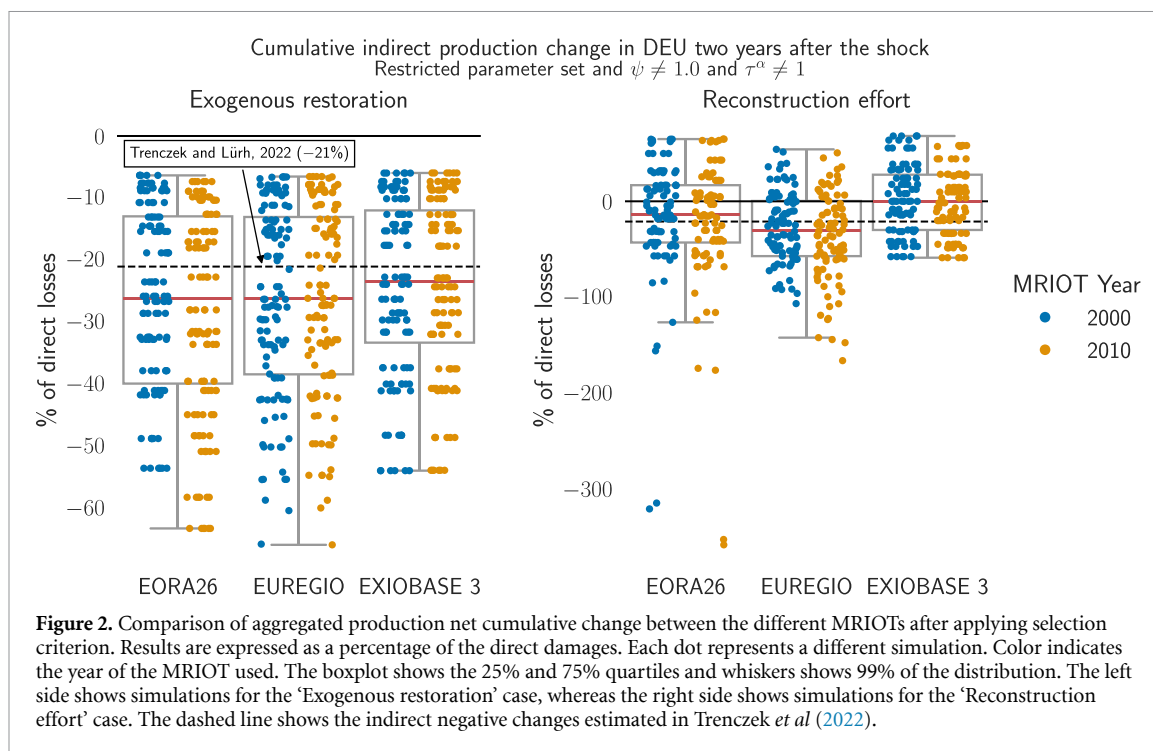


Figure 2. Comparison of aggregated production net cumulative change between the different MRIOTs after applying selection criterion. Results are expressed as a percentage of the direct damages. Each dot represents a different simulation. Color indicates the year of the MRIOT used. The boxplot shows the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

In the ‘Exogenous restoration’ case, we consistently observe negative impacts, with production changes comprised between -66% and -7% of the direct losses. Average results are comprised between -27% (EUREGIO) and -23% (EXIOBASE 3) and a majority of results represent larger losses than the -21% change found in *Trenczek et al (2022)*. The smallest losses found (no simulation results in gains in this scenario) differ by less than 1% of the direct losses, and are all close to a production change of -6% of the direct impact.

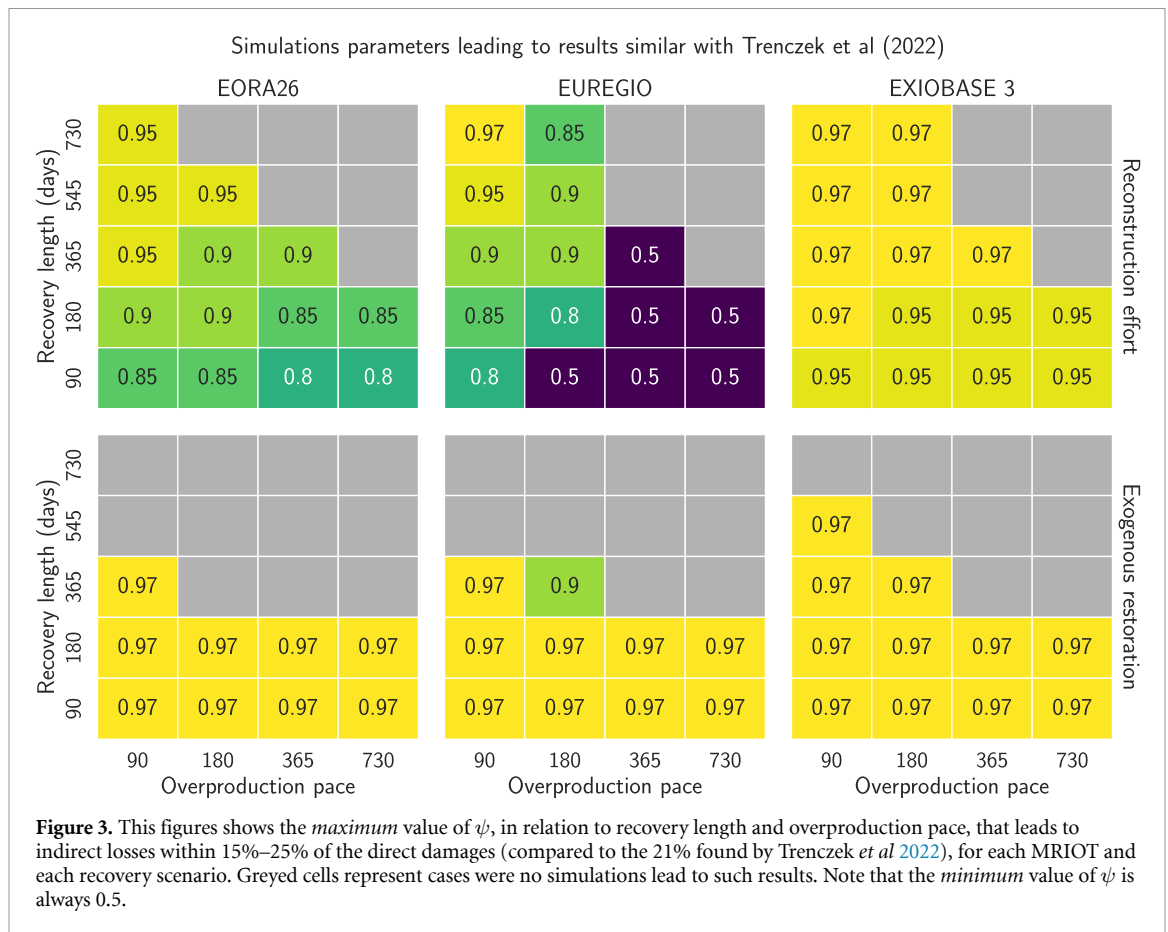
Conversely, with the ‘Reconstruction effort’ scenario, we find a mix of positive and negative impacts across all MRIOTs as well as a much wider range of impacts (production changes from -393% to $+68\%$).

In the simulations with rebuilding demand (‘Reconstruction effort’), outcomes are predominantly related to the pace of the rebuilding process (figure S2). Notably, when associated with high values of ψ , the fastest rebuilding pace (3 months), tends to lead to shortages, thereby driving the occurrence of important negative impacts. On the other hand, longest 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, for the ‘Reconstruction effort’ scenario, the variation in results between different MRIOTs becomes more pronounced for sets of parameters which lead to important negative indirect impacts. This indicates that 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 shows which sets of parameters lead to results comparable to the one from *Trenczek et al (2022)*¹². We consider comparable, all simulations leading to production changes between -25% and -15% of the direct impact (compared to the -21% found in *Trenczek et al (2022)*). Overall, this comparison with *Trenczek et al (2022)* shows that different parameter settings can lead to similar results, especially in the ‘Exogenous restoration’ scenario, as well as when employing the EXIOBASE 3 MRIOT (for both recovery scenarios).

¹² We focus on the maximum value of ψ , as we find that, given all other parameters and choices fixed, if a value of ψ lead to results similar to *Trenczek et al (2022)* then so do smaller values. This is due to the fact that this parameter either has no or very limited influence on the results, or a very significant one (see section 2.3.1).



For the ‘Exogenous restoration’ scenario, ψ has a limited influence, and cases that diverge from Trenzcek et al (2022) are essentially due to recovery length being too long (a year). Simulations with recovery length of a year (or a year and a half for EXIOBASE 3) but ‘responsive’ overproduction (90 to 180 days) also lead to similar results. The ‘Reconstruction effort’ scenario presents a different picture: the maximum possible ψ value with comparable results, differs significantly more, depending on the two other parameters, except for EXIOBASE 3. Overall, we find that longer recovery and faster overproduction pace allow for higher ψ values.

3.1.3. Per economic sector impacts

Next, we examine the per-sector production changes (figure 4). Results in this section are expressed as a percentage of the annual production of the sector.

In the absence of rebuilding demand, all sectors experience a change ranging from less than 0.00% to –0.5%, i.e. a decline.

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 its largest losses reaching changes of –1.4% and largest gains +0.4%, as opposed to the narrower range of –0.3% and –0.02% observed without considering rebuilding demand.

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 representing +1.1% of its yearly production. We attribute this result to the fact that the rebuilding demand targets mostly this sector. In some simulations, the ‘Manufacturing’, ‘Sales, Transport and Services’, ‘Agriculture’ and ‘Energy and Utilities and Mining’ sectors see modest production gains (under +0.4% of yearly production).

3.2. Shortages in the ARIO model: occurrences and implications

Due to the high impact of *shortages* on simulation outputs, we look at their frequency of occurrence and at their impact on the results (figure 5). Overall, simulations with shortages are less frequent than simulations

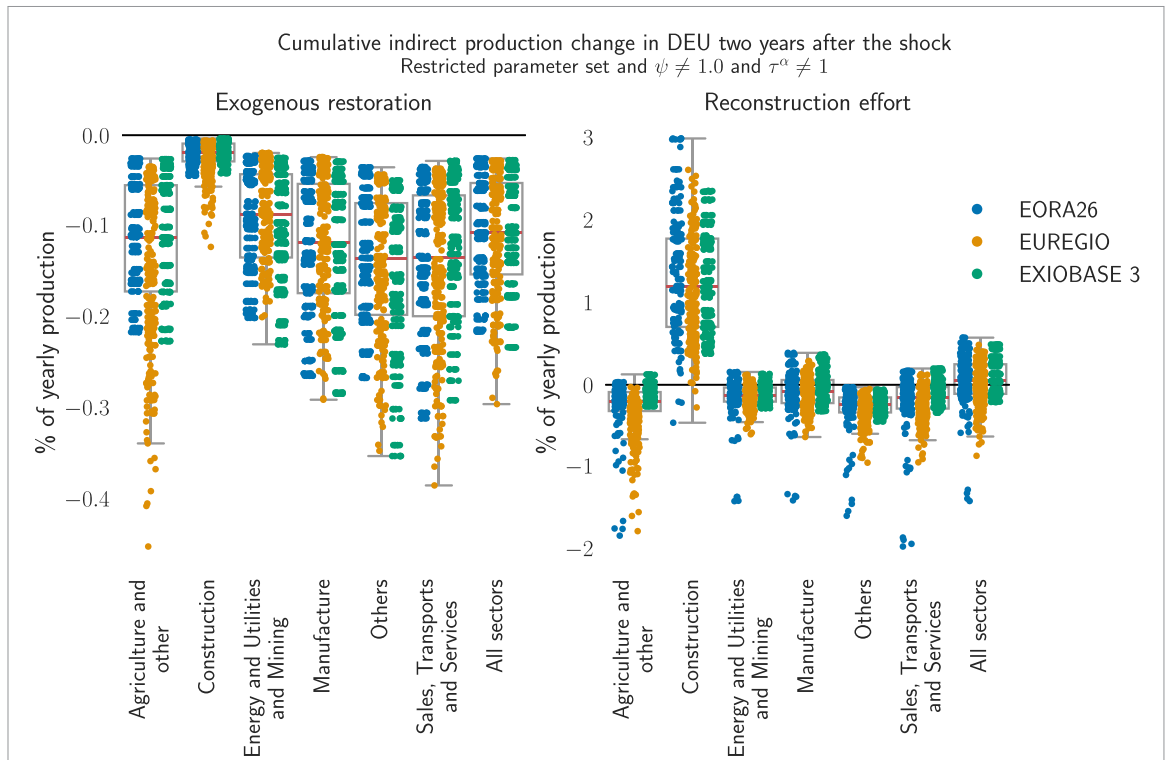


Figure 4. Comparison of per sector production net cumulative change between the different MRIOTs after applying selection criterion. Values are expressed as a percentage of the yearly production of each sector. Color indicates the MRIOT used. Boxplot shows the 25% and 75% quartiles and whiskers shows 99% of the distribution. The left side shows simulations for the ‘Exogenous restoration’ case, whereas the right side shows simulations for the ‘Reconstruction effort’ case.

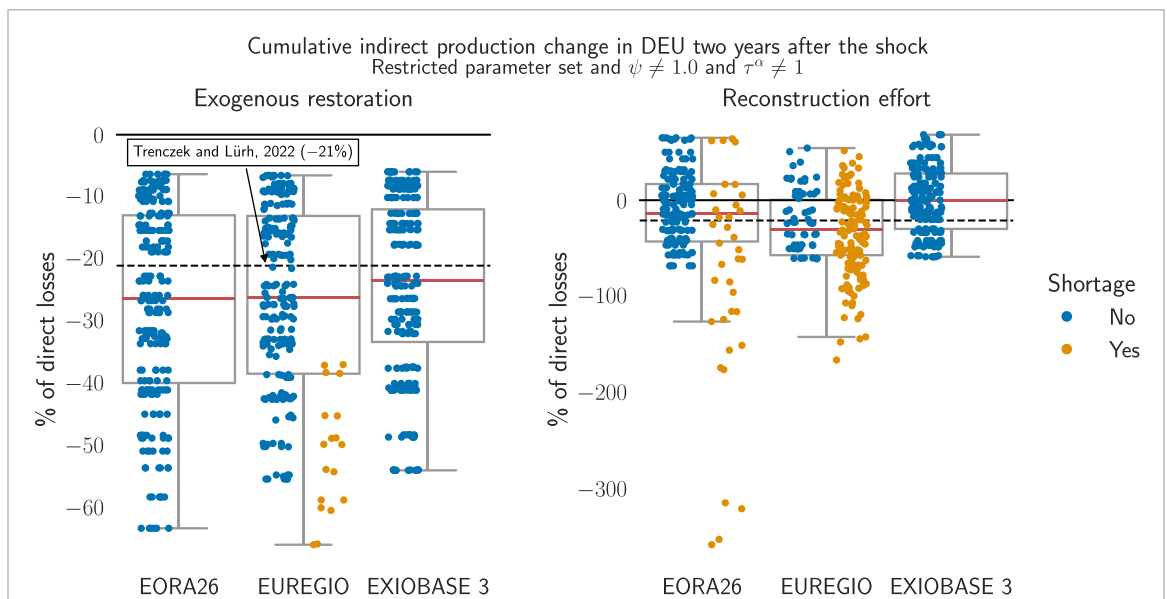


Figure 5. Influence of the occurrence of shortage on results. Results are expressed as a percentage of the direct damages. Color indicates if a shortage happened during the simulation. The left side shows simulations for the ‘Exogenous restoration’ case, whereas the right side shows simulations for the ‘Reconstruction effort’ case. Boxplot shows the 25% and 75% quartiles. The dashed line shows the indirect losses estimated in *Trenczek et al (2022)*.

without (less than 16% of the simulations). In the ‘Exogenous restoration’ case, shortages are almost absent (less than 2% of the simulations)¹³.

Conversely, simulations considering rebuilding demand show a higher incidence of shortages (34% of the simulations) and outlier results are all associated with this case.

¹³ Note that some shortages appear when looking at the sectoral level, but have negligible influence on the aggregated results.

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. This combination of factors can be interpreted as the inability of the model to answer the reconstruction demand in the short term without compromising the rest of the productive apparel.

We also observe that ARIO's sensitivity is higher when shortages occur¹⁴: for a given direct shock, as long as no shortage occur, changes in parameters values (which do not lead to a shortage), are associated with linear changes in losses. Conversely, if at least one shortage occurs within a simulation, slight changes in parameters values increase or decrease losses non-linearly. This explains the higher sensitivity of the ARIO model when assumptions are pessimistic (section 3.1.2), as well as our observation when comparing results to *Trenczek et al (2022)* in figure 3: the behaviour of the ARIO model is mostly linear and similar to a static Leontief modelling approach¹⁵ as long as assumptions on parameters do not lead to significant shortages.

Using EXIOBASE 3 does not exhibit shortages on the restricted set of parameters. Simulations using EORA26 lead to shortages in about 9% of the parameter sets, and using EUREGIO exhibit a larger share of almost 40%, notably being the only MRIOT where shortages occur in the 'Exogenous restoration' case.

It is interesting to note however that simulations using the EORA26 MRIOT and where shortages occur, often lead to relatively larger indirect losses as depicted in figure 5. In parallel, we note that multiple parameter sets were excluded from the comparison because results using the EORA26 MRIOT exceeded our criterion (see section 3.1.1) while it was not the case for EXIOBASE3 and EUREGIO.

3.3. Influence of the MRIOT choice on results

Overall, we find that the choice of the MRIOT has a different influence on the results depending on the recovery scenario used, with a higher influence of this choice with the 'Reconstruction effort' scenario. We observe these differences both in the aggregated and per sector results. We find that for similar parameters settings, different MRIOTs may lead, or not lead, to shortages, which drives the significant differences in results. This is tied to both the typology and resolution (both sectoral and regional) of the MRIOTs, as we find simulations employing the MRIOTs once aggregated to a common typology to lead to similar outcomes. The section below details these different findings.

In the 'Exogenous restoration' scenario, the choice of a different MRIOT has a limited influence on the results (see figure 2). Largest losses by MRIOT represent changes of -66% (EUREGIO), -63% (EORA26), and -53% (EXIOBASE 3), and all happen for similar parameters choices of $\tau^\alpha = 730$, $\tau^{\text{recovery}} = 730$. The value of ψ only influences results for EUREGIO, for which the largest losses are found for $\psi = 0.97$, and $\psi \leq 0.85$ consistently leads to -55% (for $\tau^\alpha = 730$, $\tau^{\text{recovery}} = 730$).

Conversely, in the 'Reconstruction effort' scenario results are more sensitive to the MRIOT used. For instance, maximum gains for EUREGIO consist in production change of $+52\%$, while they amount to $+68\%$ for EXIOBASE 3. Likewise, third quartiles are respectively at $+27\%$ (EXIOBASE 3), $+17\%$ (EORA26) and -13% (EUREGIO), average results are 0% (EXIOBASE 3), -24% (EORA26) and -47% (EUREGIO) and first quartile is -30% (EXIOBASE 3), -43% (EORA26) and -74% (EUREGIO).

Overall, we find the choice of the year of the MRIOT used (2000 or 2010) to lead to limited changes in the results, with the exception of EORA26 in the 'Exogenous restoration' case, where negative extremes shift from -53% (year 2000) to -63% (year 2010) and EUREGIO in the 'Reconstruction effort' case, where negative extremes shift from -138% (2000) to -189% (2010). For EXIOBASE 3 the only significant difference is found for the maximum gains in the 'Reconstruction effort' scenario (68% for 2000 and 58% for 2010).

At the sector level and for the 'Exogenous restoration' scenario (figure 4), we find differences in average results between MRIOTs to be less than 0.05 percentage points for all sectors, with the notable exceptions of the 'Construction' sector which shows average change of -0.02% for EORA26 and EXIOBASE 3, compared to -0.19% for EUREGIO. Actually, all results for the 'Construction' sector using EUREGIO represent larger losses than the maximum losses found with the two other MRIOTs. Maximum losses are also noticeably larger for the 'Agriculture' sector when using EUREGIO (-0.4% change compared to around -0.2% for EORA26 and EXIOBASE 3).

With the 'Reconstruction effort' scenario, disparities in outcomes between sectors across different MRIOTs become more pronounced. For instance, using EUREGIO, the 'Agriculture' sector exhibit results ranging from -1.9% to 0.0% change, whereas the range narrows to -0.4% to $+0.1\%$ when employing EXIOBASE 3.

What creates a larger difference in results across different MRIOTs choices stems from them leading to shortage situations more or less easily, and as shortages are mostly seen in the 'Reconstruction effort'

¹⁴ which is shown by the significantly larger spread of results when shortages occur.

¹⁵ Indeed, *Trenczek et al (2022)* use a static Leontief model to derive their results.

scenario, so are the major differences. Figure 6 shows the evolution of production of the ‘Agriculture and other’, ‘Construction’ and ‘Manufacture’ sectors, for a specific simulation, for both recovery scenarios and all three MRIOTs. Shortages are easily observed in the figure by the visible inflexion and drop in production output. In the ‘Exogenous restoration’ scenario, we note the occurrence of a shortage (of limited influence on production) in the ‘Agriculture and other’ for the EUREGIO MRIOT scenario contrary to the two other MRIOTs, which explains the greater losses per sector observed in figure 4 for EUREGIO and this scenario.

Also note the difference in direct impact denoted by the initial drop of production. This difference is tied to the distribution of the direct damages in proportion to the GDP (see section 2.4). As EUREGIO represents the German federal states instead of Germany as a whole, this distribution differs, and, in this case, increases direct impacts on Agricultural sectors.

With the ‘Reconstruction effort’ scenario, shortages hit both the simulations employing EORA26 and EUREGIO MRIOTs, while not affecting the one with EXIOBASE 3. Also, in this scenario, production drops are more profound. This observation relates well with the disparities of losses found between the three MRIOTs with the ‘Reconstruction effort’ scenario.

MRIOTs regional and sectoral resolution has been shown to influence results (Henriet *et al* 2012). Thus we also examined a subset of simulations, where we aggregate the different MRIOTs to our common typology before running the simulations rather than aggregating the results afterward. This approach aimed to further understand how the characteristics of MRIOTs influence the outcomes (see figure S16). We find that the resolution of sectors and regions indeed plays a role in the results as the notable differences across MRIOTs in the ‘Reconstruction effort’ scenario we found only emerge when MRIOTs are not pre-aggregated. For the EUREGIO MRIOT the regional resolution alone induces differences in results, whereas for EORA26, the initial typology of sectors induces the differences.

The sub-country resolution of EUREGIO, associated with the higher incidence of shortages, and the fact that such shortages are not present when regions are aggregated to the whole country (figure 6), highlights the effect of such sub-country resolution. Interestingly, the high resolution of sectors (163) of EXIOBASE 3 is not associated with a high incidence of shortages, as would suggest the results observed with EORA26, for which shortages only occur with the full 26 sectors. This points out that while differences in the resolution of sectors and regions appear to have a significant influence on outcomes, it is not the sole aspect explaining the differences in results.

3.4. Influence of the parameters on results

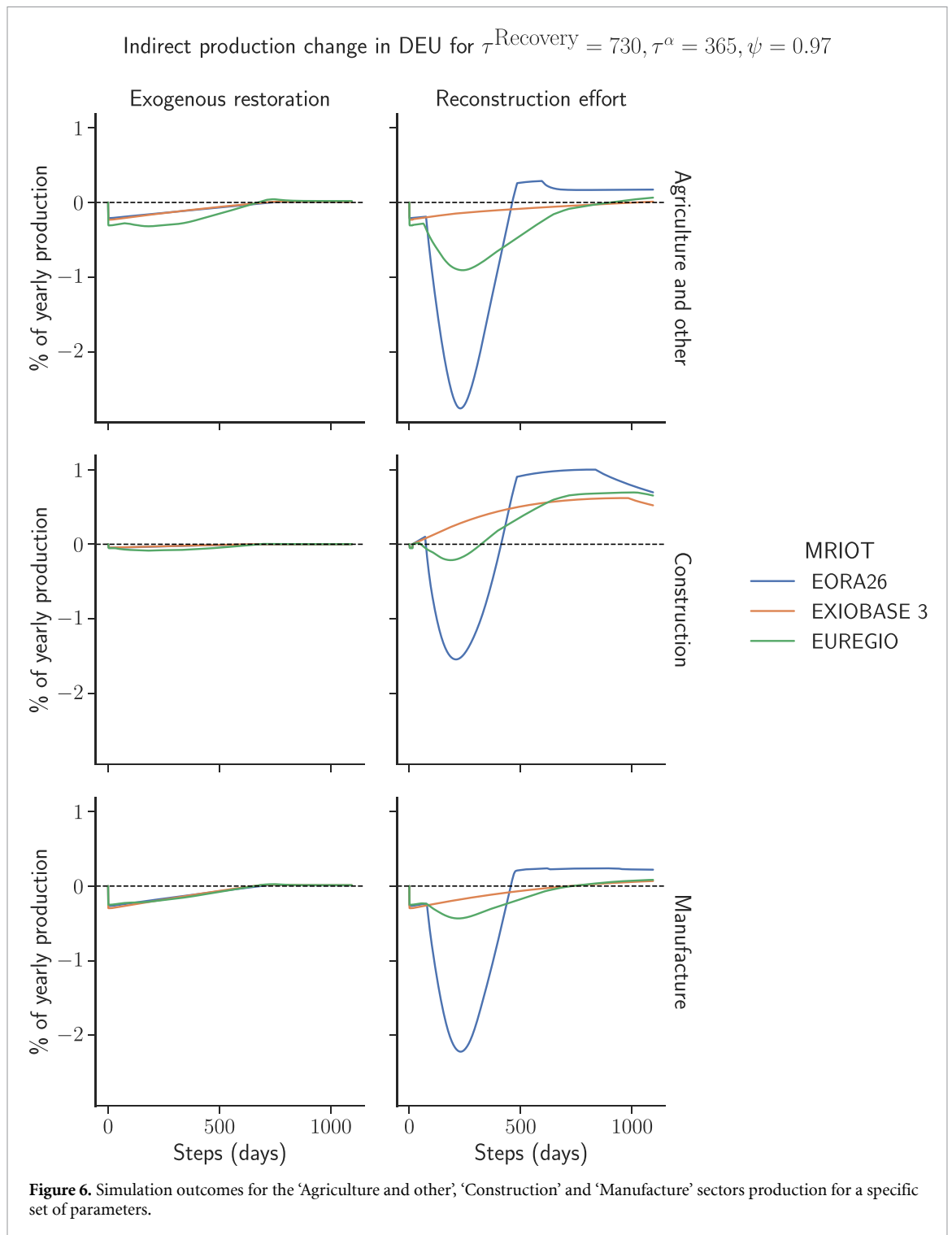
In this section, we describe the most noticeable effects of each parameter on results. In order to get a general characterization of the model and exhaustiveness, we observe outcomes for both the whole simulation set and the restricted set (see section 3.1.1). Similarly to section 3.1.2, change in production from indirect impacts are expressed as a percentage of the direct impact, with positive percentages representing production gains, and negative percentages representing production losses.

3.4.1. Heterogeneity parameter ψ

Parameter ψ overall does not influence the results significantly in the ‘Exogenous restoration’ case. This is expected since there are almost no shortages in this scenario and as ψ only influences the results when shortages occur. In the whole simulation set, when the value ψ is strictly above 0.9 the maximum indirect losses observed significantly increase. For instance, for the EORA26 simulations, when the value shifts from 0.9 to 0.95, results shift from around -112% change to more than -510% , setting ψ to 0.97 further shifts results to -655% , and with a value of 1, production changes reach -2230% of the direct impact. A similar behaviour can be observed for EXIOBASE 3 (results shift from -125% (0.9) to -400% (0.95), -672% (0.97) and -1800% (1.0)). We note however, that results with the EUREGIO MRIOT appear relatively unchanged.

Conversely, when looking at the restricted set, changes in results are only observed for the EUREGIO MRIOT (in concordance with this MRIOT being the only one for which shortages occur in this case), but these changes are only noticeable for the maximum losses when using values above 0.9 (as production decreases by another 10% of the direct losses).

In the ‘Reconstruction effort’ scenario, changes in the value of ψ below 0.85 has marginal if no impact on the results. For larger values, we note a behaviour similar to the one observed in the ‘Exogenous restoration’ scenario, with an even more pronounced effect, i.e. the increase in maximum indirect losses is more significant (For instance, for EORA26 and $\psi = 0.9$, production change is about -855% , almost -3000% for $\psi = 0.95$, and almost -5000% for $\psi = 0.97$). In addition, contrary to the ‘Exogenous restoration’ case, similar significant changes are also observed for the EUREGIO MRIOT, albeit to a lesser extent (results shifts from -180% (0.85) to -1350% (0.97)). In comparison, results spread for the EXIOBASE 3 MRIOT are less pronounced and maximum losses are much lower (with -60% change for $\psi \leq 0.9$, -110% for 0.95 and -343% for 0.97).



For the restricted set of parameters, changes in results are essentially observed for EORA26 and EUREGIO, and similarly, are more pronounced for EORA26. Interestingly, increasing the value of ψ significantly reduces the maximum gains (increases the minimum losses) when using EUREGIO, starting as soon as changing ψ from 0.5 to 0.8.

3.4.2. Overproduction pace τ^α

The parameter τ^α (which denotes the pace of overproduction), has a rather straightforward influence on the results, with the exception of the special case of 1 day in the ‘Exogenous restoration’ case, where the model appears to behave erratically, as we find outcomes representing both the largest losses and gains. Otherwise, we observe the expected influence, i.e. that faster overproduction reduces losses and increases gains in both

the ‘Exogenous restoration’ and the ‘Reconstruction effort’ scenarios, and for both the whole set and the restricted set.

3.4.3. Characteristic time of recovery

We find the characteristic time of recovery to play a key role. In the ‘Exogenous restoration’ scenario, faster recovery result in lower maximum losses, although when looking at the whole set of simulations, this observation is eclipsed by the simulation where $\tau^\alpha = 1$. The influence of the parameter also appears to be very similar across the different MRIOTs, which is especially visible for the restricted set.

With the ‘Reconstruction effort’ scenario, for the whole set of simulations, we observe that increasing the time overall reduces the spread of the outcomes, that is largest gains are smaller for longer recovery characteristic time, but largest losses are also significantly smaller (the effect on maximum losses is actually more pronounced than on maximum gains).

The reduction in the largest losses is due to longer recovery times leading to lower rebuilding demand per step, which decreases rationing on intermediate demand and thus reduces the occurrence and intensity of shortages.

Conversely, the reduction in the largest gains is explained by the fact that the demand stock for reconstruction is not entirely fulfilled by the end of the simulation for long recovery times. This means that higher gains would probably be observed if the simulations lasted longer. The ARIO model is however less relevant for such longer period, as such these results should be interpreted carefully.

Using the EORA26 table also show significantly more sensitivity to this value than the two other MRIOTs (outcomes shift from a range of -7815% – $+65\%$ for $\tau^{\text{Recovery}} = 90$ to -3200% – $+17\%$ for $\tau^{\text{Recovery}} = 730$ for EORA26 and -2900% – $+65\%$ for $\tau^{\text{Recovery}} = 90$ to -980% – $+24\%$ for $\tau^{\text{Recovery}} = 730$ for EXIOBASE 3).

For the restricted set, most of the high losses corresponding to very short recovery time are excluded, thus the influence of longer time is less visible and overall closer to the effect found for the ‘Exogenous restoration’ scenario.

3.4.4. Historical parameter values

We also look at the results of simulations restricted to the historical parameter values found in Hallegatte (2013) for ψ (0.8) and τ^α (365 days). The range of results for this even more restricted set falls between -58% and $+12\%$ of the direct losses to the exception of a notable outlier for EUREGIO in the ‘Reconstruction effort’ case where losses amount to 102% of the direct losses (see figure S1). Results for the EUREGIO table in the ‘Reconstruction effort’ case are actually significantly different from all other results, ranging from -102% to -35% , whereas all other results are within -60% to 12% .

Differences between the two recovery scenarios are less visible, largest losses all range within -65% to -45% of the direct losses (except for EUREGIO as previously mentioned). Average losses are slightly larger in the ‘Exogenous restoration’ case (around -30%) compared to the ‘Reconstruction effort’ case (-20%). However, all average results are similar with and without rebuilding demand: between -25% and -30% of the direct losses, again with the notable exception of simulations using EUREGIO MRIOT when considering rebuilding demand, where the average result is -45% .

Differences between using year 2000 or 2010 are marginal, although losses are overall slightly more pronounced for year 2010.

We also note these results to be reasonably close to the -21% value found by Trenczek et al (2022).

3.5. Impacts on other regions

We also examine the indirect impacts in other regions to account for cross-border impacts (see = figures S5, S6, S7, S8, S9, S10, S11 and S12). When not considering a rebuilding demand, we find that most simulations result in production gains, although these gains do not exceed $+5\%$ of the direct damages¹⁶. In rare instances where indirect impacts result in losses, they represent less than -1% 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), $+0.030\%$ in China ($+13\%$ of the initial damages) and $+0.002\%$ of yearly production in USA ($+2\%$ of the initial damages). Some simulations result in noticeable losses. For instance in the ROW region, 4 simulations lead to losses higher than -10% of the direct losses. Note here, that the ROW region aggregates the losses of a large number of regions. When compared to the actual size of the ROW economy, the highest indirect damages represent less than -0.01% of yearly production. For France, highest indirect impacts are less than -0.03% of yearly production.

¹⁶ Such gains are explained by shifts in trade relations across regions following the shock.

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 inter-regional 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.

4. Conclusions

In this study 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 share profound similarities with numerous other models (Koks and Thissen 2016, Otto *et al* 2017, Shughrue and Seto 2018, Colon *et al* 2019). 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, and that the MRIOT used as a representation of the economy also significantly influence the results observed.

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 +68% (i.e. gains) to -394% (i.e. losses) of the direct losses. When we do not take into account this demand, total production change ranges only from -66% to -6% of the direct losses.

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 (such as heatwaves, droughts, or power blackouts), may be studied with models such as ARIO without having to solve this issue as they presumably do not create a rebuilding demand.

The economic data used as input to the model appears to play an important role in the simulation results, especially when rebuilding demand is accounted for. We find that using EXIOBASE 3 leads to indirect impacts lower in average than using EUREGIO and EORA26. These two tables also show more variability in the results, tied with the presence of important negative outcomes. We also find that the observation of such negative outcomes is tied with the resolution of sectors and regions for EORA26 and EUREGIO, hinting that the aggregation of MRIOTs can significantly influence results. In particular, aggregating MRIOTs to a coarse set of regions or sectors, or both, may significantly change the observed outcomes.

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. Choosing a short rebuilding duration of three months can especially lead to large indirect impacts: as rebuilding demand per step is higher 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 using a value of 0.97 lead some results to far exceed the order of magnitude of the direct damages especially when rebuilding demand is considered.

Our different results highlight an important aspect of the ARIO model: it can either have a linear behaviour with a 'smooth recovery'—and produce results similar to traditional IO models, or a non-linear one, where shortages occur and indirect losses are significantly higher. A major driver or whether the model falls in one behaviour or the other is the presence (or absence) of an endogenous reconstruction demand.

5. Discussion

Different modeling choices on the reconstruction demand after a natural disaster can be found in the literature, in different papers (e.g. Koks *et al* 2014, Wang *et al* 2020 which both consider such a demand contrary to Willner *et al* 2018). These two choices represent extreme cases, as it may be expected that reconstruction will lead to at least some new demand (see for instance the empirical work by Hsiang 2010), when the disaster leads to physical damage. 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.

We find 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 which aligns with existing studies on the impacts of natural disasters (Hallegatte and Przulski 2010, Klomp and Valckx 2014, Jha *et al* 2018, Kunze 2021, Noy and Strobl 2022). 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 MRIOT. In particular, we suggest that, as comparison with observation on indirect impacts is difficult, the ARIOT 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. We argue that this suggestion is even more relevant in the case of future extreme events in the context of climate change where comparison with observation is not possible at all. Thus, future studies should focus more on exploratory work, prospective analysis and qualitative results than on quantified outcomes, as quantitative results are extremely sensitive to modeling choices, which cannot be precisely calibrated. Such work, encompassing a range of reasonable hypothesis would allow to study which future condition could lead to extreme indirect impacts with better confidence.

Our results on the unaffected regions tend to show an overall increase of their production—albeit relatively small compared to the size of their economy. This finding should be taken with caution as inter-regional trade dynamics are not the focus of this study, and while we allow for inter-regional substitution within the ARIOT model, it remains marginal and with simple assumptions. A deeper focus on how unaffected regions react to a shock in another region (for instance by providing relief, or by actively seeking to replace failing suppliers of the affected region), would bring valuable information on the response to a shock at a more global scope.

Considering MRIOTs, we note that 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, with limited comparison. We find that different resolutions of sectors or regions can significantly influence results. Our results do not imply that MRIOTs with a higher resolution of sectors and regions lead to more realistic results than ones with a coarser typology. Indeed, while higher resolution may seem preferable, it may come with decreased quality and precision. Associated with high sensitivity of the ARIOT model, it may lead to an overall worse estimation of the propagation of the initial shock. This underscores the importance of using and comparing multiple MRIOTs and exercising caution when aggregating them. This also supports future work on the disaggregation of MRIOTs such as Wenz *et al* (2014), to further understand the implications of using coarse or fine economic data.

Our analysis did not include parameters related to inventories, such as size and resupply time and heterogeneity between sector (or even region), 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 change quickly and how supply chains are put in difficulty (Maital and Barzani 2020, Guenette *et al* 2022). This raise the importance of looking at deeper changes in MRIOTs and how it can influence vulnerability to indirect economics impacts.

Data availability statement

This study uses the `boario` open-source python implementation of the ARIOT model (version 0.5.10), documented at <https://spjuhel.github.io/BoARIO/>.

All MRIOTs used throughout the study are available on their respective websites.

The study can be entirely reproduced using the Snakemake pipeline (Köster and Rahmann 2012) available at <https://github.com/spjuhel/BoARIO-Sensitivity>. Due to the impracticality of hosting the entirety of the raw results on an open platform, they are only available upon request to the corresponding author.

The data that support the findings of this study are openly available at the following URL/DOI: <https://zenodo.org/records/13305448> (Juhel 2024b).

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