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Economic impacts of natural hazards and complexity science: a critical review

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2022/13 May 2022
ISSN(ONLINE) 2284-0400

Economic impacts of natural hazards and complexity science: a critical review

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May 4, 2022

Abstract

Extreme natural hazards represent, together with crises and wars, the most disruptive phenomena for economic activity. Their economic impact has been shown to be remarkable, long-lasting, and growing over time, though the exact mechanisms at stake are challenging to isolate and quantify. As these trends are likely to endure as global warming becomes more severe, the need for appropriate modeling of both short and long-run impacts of natural disasters is becoming increasingly pressing. Building on a mounting number of empirical works, we here provide a critical review of the modeling approaches traditionally employed in the related literature. Although with notable exceptions, conventional methods are generally based on Input-Output or Computational General Equilibrium models. These approaches, while analytically sound, are structurally ill-suited to capture certain aspects of natural hazard consequences. Systemic responses to such extreme events are typically characterized by complex interactions among heterogeneous agents, adaptive behavior, and out-of-equilibrium dynamics. We here argue that complexity methods can represent a valid alternative to bridge this policy-relevant gap. In particular, Agent-Based Models offer a powerful toolkit to account for non-linear geographical and temporal interdependencies, the presence of hysteresis and path dependency, the impact of technology changes, and can be fruitfully employed as laboratories for adaptation and mitigation policies.

Keywords: Natural disasters, Socio-economic networks, Complexity, Agent-based models.
JEL Classification: C63, C67, C68, Q50, Q54.

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1 Introduction

Natural disasters are one of the most disruptive phenomena for economic activity. In addition to the immediate destruction of buildings, infrastructures, and physical capital (often referred to as *direct damages*, Meyer et al. 2013), these events often bring about enduring losses, as a consequence of interrupted businesses and supply chain disruptions (*indirect damages*). These perturbations to the economic activity can be substantial, and can easily exceed the losses experienced in the immediate aftermath of the event (Kroll et al., 1990; Tierney, 1997). Barro (2006, 2009) has shown that rare economic disasters have larger consequences in terms of welfare with respect to much more frequent, bus less sizable, economic fluctuations. Although with substantial regional and temporal differences, there is growing evidence that this might hold true even more in the case of natural hazards. Indeed, their economic impacts are not only remarkable in magnitude, but typically persistent over time. Hsiang and Jina (2014) estimate a reduction in per-capita income of 7.4% as a consequence of a 90th percentile cyclone, an effect still detectable 20 years after the event. The negative effect jumps to 14.9% when considering extreme cyclones (99th percentile). By comparison, a civil war is estimated to lower income by 3%, while a banking crisis can arrive up to 7.5%; in both cases, the effects are generally reabsorbed within 10 years (Cerra and Saxena, 2008). Worryingly, there is growing evidence that the economic impacts of weather-related natural hazards - especially those arising from the most severe events - are mounting (Coronese et al., 2019; Grinsted et al., 2019). While it is to date unclear whether these trends can be attributed to anthropogenic climate change, there is little doubt that global warming will entail more frequent and intense weather extremes (Van Aalst, 2006; Field et al., 2012; Otto et al., 2018). Thus, the accurate study of the determinants of both short and long-run economic effects of natural disasters is of paramount importance and highly policy-relevant.

Despite the blossoming literature around the topic, our understating of the economic consequences of natural disasters is still limited. Available data sources have allowed researchers to work with rather accurate figures of direct damages at the global level (EM-DAT Database, MUNICH RE NatCat, SWISS RE Sigma), leading to a generalized consensus about the negative short-run impacts of natural disasters (Cavallo and Noy, 2009). However, the general lack of disaggregated data, e.g. by economic sectors and household income classes, severely limits the assessment of heterogeneity in impacts. A detailed understanding of direct damages is vital for the construction of damage functions, which link hazard magnitude (e.g. wind speed, water depth, storm surge) to the experienced losses (Nordhaus, 1992; Hsiang et al., 2017; Prahl et al., 2018; Hallegatte et al., 2011). While such functions are typically scale-dependent, location-specific, and varying over time (because of e.g. more resilient infrastructures or adaptive behavioral responses, Prahl et al. 2016), reduced form versions (usually concave and upwardly curved) are routinely employed in standard Integrated Assessment Models, which serve as one of the main operative tools for climate cost-benefit analysis.

Indirect losses, and long-run effects on economic growth, are even harder to estimate, as they require comparing the observed outcome against a theoretical counterfactual - what would have happened if the shock did not hit. While robust econometric techniques have shed light on the sign and the magnitude of these effects (Section 2), little has been explained in terms of underlying economic dynamics, which often need carefully designed modeling. The two most common modeling approaches are Input-Output (IO) and Computable General Equilibrium (CGE) models. IO models (IOs henceforth, Section 3.1) represent the economy (national or regional) in the form of tables describing the flows of products between the various sectors (including imports and exports). Because the production structure can be considered rather fixed in the short term, these models are routinely employed to assess how disruption of certain nodes in the supply chain propagates to the overall economy. IOs are however not well equipped to capture economic dynamics that extend beyond the immediate aftermath of the event, as they do not include any type of behavioral response, long-run adjustment, or technical change, thus likely leading to an overestimation of damages. To overcome these limitations, scholars usually rely on CGE models (CGEs henceforth, Section 3.2), which are rooted in the neoclassical tradition of the general-equilibrium paradigm, entailing profit-utility maximization, rational expectations, and market-clearing assumptions. Models departing from these premises are instead likely to largely underestimate the effective costs of sizable hazards, by assuming optimal behavior and immediate market adjustments (Meyer et al., 2013).

Natural disasters are indeed complex phenomena, involving non-trivial interactions among heterogeneous actors, non-linear responses, abrupt changes, and out-of-equilibrium dynamics. Recently, the complexity approach has gained momentum in multiple scientific disciplines, including economic and social sciences (Vicsek, 2002). We here argue that complexity methods can represent a powerful tool in order to model the impacts of such rare, but potentially catastrophic events. In the broadest sense, a complex system can be described as a system in which its aggregate properties cannot be directly inferred from those of its components. Among the various analytical methodologies developed within the complexity perspective, the most promising for hazard-related modeling is certainly that of Agent-Based Models (ABMs).[1] ABMs have extended beyond the realm of natural sciences, and numerous applications are blossoming within the field of economics (see e.g. Dosi et al. 2010 modeling innovation dynamics, Filatova et al. 2013 discussing the modeling of human-natural systems interactions). These models are essentially pieces of software simulating the evolution of a complex system, as a result of the interaction of various agents among themselves, and with the surrounding environment (intended as natural, institutional, climatic, etc. . .). Indeed, part of their attractiveness lies in their ability to accommodate a number of features of real-world economic systems, without resorting to controversial assumptions, which are especially implausible in the aftermath of a natural disaster. In particular, they allow modelers to relax core assumptions of the CGE paradigm:

- *Rational expectations vs heuristics*: CGEs extensively rely on optimization schemes (profits for firms, utility for households) to model inter-temporal choices under various degrees of uncertainty. The formalization of how economic actors deal with uncertainty about future events is usually referred to as *rational expectations* (Muth, 1961). In this view, agents are assumed to be able to fully enumerate all the possible future states of the world and to assign a probability to each one. Further embedded with full knowledge of the modeled economic system and of their own objective functions, agents then compute the current expected value of all possible trajectories and optimize accordingly. In the real world, the amount of information needed to assign relative probabilities to each future event is so vast to render this formalization, at least, highly unrealistic. In several cases, the uncertainty is so deep that it is even impossible to determine the support of the distribution of future events (*deep* or *Knightian uncertainty*, Knight 1921). Indeed, as shown by Kahneman (2002), human beings, and firms as well, tend to act in ways that are quite distant from those predicted by the rational paradigm (a paradigm often referred to as *bounded rationality*), displaying behaviors such as loss aversion and miscalculation of small

[1] Other methodologies have been often applied within the complexity approach, see e.g. Naqvi and Monasterolo (2021) for a network analysis, and Hallegatte et al. (2007) for a system dynamics one.

probabilities. As stressed by scholars in the evolutionary economic literature, economic actors tend to deal with complex situations by employing heuristics (e.g. copying a successful strategy, spending only a certain fraction of income on housing, etc...) and by routinizing complex tasks (Nelson, 1985). These considerations are of remarkable importance when investigating the aftermath of disastrous events. After such sudden and abrupt changes, individual behavior is not only characterized by limited information: abnormal solidarity and assistance, radical uncertainty, and shifts in governance and political processes drive behavioral responses and endogenous changes in preferences (Hallegatte and Przyluski, 2010), as well as heterogeneous variations in perceived risk (Filatova et al., 2011b). For instance, consumers may reduce demand as a sign of sympathy for individuals affected by disasters (Okuyama, 2004). Also, firms' decisions (investment, adaptation, and mitigation) are carried out in a context of bounded rationality, given the uncertainty about future demand, possible trajectories of technical change, and the complex interactions between R&D efforts, substitution or upgrading of damaged capital, governmental mitigation strategies (such as insurance schemes or credit availability) and future supply network structures (Safarzyńska et al., 2013). In other words, agents' behavior is not invariant with respect to the occurrence of a disaster and can be rarely characterized as rational. This does not necessarily imply sub-optimal outcomes: employing heuristics can indeed represent a rather efficient way to make choices when facing complex situations characterized by deep uncertainty (Gigerenzer and Gaissmaier, 2011). In this perspective, ABMs flexibly allow modelers to embed virtually endless behavioral rules, rigorously built upon empirical evidence.

- *Representative agent vs emergent properties*: One of the theoretical backbones of the CGE approach is the representative agent assumption. Because of analytical tractability needs, these models often postulate a one-to-one mapping between individual and collective behavior, *de facto* removing heterogeneity and interaction among actors from the analysis. To assign a complex system with characteristics proper to its individual components is a simplification that is questionable even on a theoretical ground (Kirman, 1992), and severely limits the understanding of underlying mechanisms (Fagiolo and Roventini, 2016). Just to provide a concrete example, adaptation decisions in the wake of a disaster are found to be very heterogeneous, differing both in space and time, and can rarely be captured by a representative, optimizing agent (Malawska and Topping, 2016; van Duinen et al., 2016).[2] Empirical studies have indeed found a high level of heterogeneity in individual responses to environmental risk (see e.g. Filatova et al. 2011b). Ruling out interaction and information sharing can also result in a critical mismeasurement of aggregate risk, due to collective adaptive behavior (Aerts et al., 2018). In ABMs, aggregate properties of the system arise instead as *emergent properties*, as a result of the interaction between heterogeneous agents and without any *ex-ante* imposition, through a genuine bottom-up approach. In particular, network models have produced a fruitful body of literature assessing the vulnerability of complex systems to external shocks (see e.g. models of macroeconomic risk from financial imbalances, Battiston et al. 2012), and can be integrated into ABMs to obtain a dynamic modelling of contagion effects.

- *Equilibrium vs coordination*: After having specified the behavioral rules governing the system, models in the neoclassical tradition are typically "closed" through market-clearing assumptions.

[2]For a recent and comprehensive review on empirical findings, behavioural theories and ABMs in the context of drought risk assessment, see Schrieks et al. (2021).

Markets are assumed to always reach the equilibrium, through appropriate adjustments of price and quantities. As a result, in the long-run, the economy naturally gravitates along a balanced-path that is deterministically predetermined, while short-run fluctuations are explained through exogenous shocks. In contrast, in ABMs the robust regularities observed in the real world emerge as the result of - possibly imperfect - coordination attempts by boundedly rational agents (Dosi and Virgillito, 2021), without any imposition of market-clearing, thus in a state of *persistent disequilibrium*. Indeed, if the occurrence of a natural disaster can be considered fairly exogenous, its impacts are usually not (Cavallo and Noy, 2009), as they are largely influenced by mitigation and adaptation measures put in place by the local populations, which are in turn dependent on behavioral responses, income levels, institutional setting, and past exposure. Even then, growing evidence is pointing towards persistent effects of natural disasters on aggregate income, thus rejecting the notion of a gradual return to pre-shock levels of growth - or even greater, as in the so-called "build-back-better" hypothesis (Hsiang and Jina, 2014). *Path dependency* and *hysteresis* effects extend well beyond aggregate income, as in the case of permanent changes observed in local labor and housing markets (e.g. after the Katrina hurricane Vigdor 2008) or shifts in labor structure due to heavy migration (e.g. following the 1992 hurricane in the Hawaii Coffman and Noy 2012), although it is often difficult to disentangle the pre-shock trends with those caused by a disruption (Cavallo et al., 2011). Standard CGE approaches are in fact designed to study the long-run steady state of an economy, but struggle to assess the complex non-linearities arising after such large events (Naqvi and Rehm, 2014a). These situations happen in fact out-of-equilibrium, when prices do not adjust and markets do not clear (Otto et al., 2017). As argued by Noy et al. (2018), economies are constantly changing, and they are even more so after natural disasters, where agents and policy reactions can change the very own economic trajectory of the region. For instance, the size and composition of the population may change (Vigdor, 2008), firms may or may not upgrade their capital (Hallegatte and Dumas, 2009a), and regional economies might get stuck into poverty traps. From this point of view, ABMs represent a powerful laboratory to generate reliable synthetic counterfactual scenarios.

In what follows, we first summarize the existing empirical literature about the short and long-run impacts of natural disasters, concentrating on the latter (Section 2); we then analyze in-depth the dominant modeling approaches (Section 3); finally, we move to the analysis of existing ABMs of disaster risk and impact assessment (Section 4), and to the discussion of future avenues of research in this area (Section 5).

2 What is there to be explained

Econometric techniques are routinely employed to investigate both short and long-run impacts. They can be a powerful test-bed for competing theories and have undoubtedly advanced our understanding of the size and the direction of disaster impacts. Nonetheless, such non-structural statistical tools suffer the lack of an impact theory, leading to difficulties in distinguishing between direct and indirect losses (Rose, 2004a), and in understanding in which way losses in different sectors depend on each other. Indeed, reduced-form estimates of disaster losses from econometric models remain often silent about the channels of transmission leading to substantial indirect damages (Koks et al., 2016).

Hazard risk is typically defined as the product of the hazard probability (the geographical-specific probability of facing an event of a given physical magnitude), the exposure (the amount of wealth and persons possibly affected by the disaster), and the vulnerability (the actual loss experienced when facing a given hazard, measuring the capability of withstanding a certain phenomenon). In order to investigate determinants of direct losses, scholars often express experienced damages as a function of a set of covariates, including disaster magnitude, measures of exposure (e.g. estimates of capital at risk, proxies for economic activity, local population), and vulnerability measures. Vulnerability measures are of particular interest, as they can proxy policy intervention. Direct impacts appear to be linked with country size, as bigger nations, while having higher exposure, are more capable of putting in place governmental transfers, inter-regional mitigation policies, and absorbing migratory phenomena (Cavallo et al., 2010). Institutional factors (such as the ability to preserve property rights, openness to trade, and education levels) can also reduce direct impacts (Kahn, 2005; Toya and Skidmore, 2007; Cavallo and Noy, 2009). On the other hand, higher levels of inequality tend to augment it (Anbarci et al., 2005), as they exacerbate coordination problems in the collective actions needed to reduce hazard risk.[3]

Because economies evolve over time, estimating the medium or long-run impacts induced by the occurrence of an exogenous event requires constructing a valid counterfactual to compare against observed data. Early literature (Skidmore and Toya, 2002) relied on the use of cross-sectional analysis relating economic outcomes to disaster indicators while controlling for potential determinants of growth. This type of approach is however problematic, due to the potential presence of omitted variable bias when determinants of economic outcomes are not included in the model but are correlated with disaster measures (Botzen et al., 2019). Hino and Burke (2021) investigate the effect of flood risk on house prices and shows how opposite results are obtained when exploiting both cross-section and temporal variability, compared with studies exploiting only the former. More recent approaches tend instead to rely on different flavors of difference-in-differences methods (see e.g. Cerra and Saxena 2008; Belasen and Polachek 2009), which are instead quite sensitive to the appropriate choice of the control group (Noy et al., 2018). This is usually accomplished either through composite fixed effects flexibly capturing pre-existing trends (Zivin et al., 2020) or through the creation of synthetic control groups by e.g. propensity score matching techniques (Deryugina et al., 2018).

Overall, there is mixed evidence on the long-run effects of natural disasters. These divergences do not depend solely on the statistical methodology employed, but also on the aggregation level of analysis, the geographical scale and the intrinsic characteristics of the economy under investigation. Evidence of long-run impacts is especially hard to spot when investigating country-level indicators. While both Jaramillo (2009) and Cavallo et al. (2013) report no statistically significant impacts, Loayza et al. (2012) reveal long-run persistent effects in developing countries. There seems to be little support for the notion that natural disasters might trigger virtuous effects on aggregate variables, in the form of renowned capital, ameliorated urban planning, and better infrastructures. This hypothesis is often referred to as "build back better". Some evidence is reported only for modest disasters taking place in high-income countries (Crespo Cuaresma et al., 2008). Trade-offs with short-run losses may nonetheless arise, as the "creative destruction" scenario often involves accurate and lengthy planning, thereby possibly interacting with resources destined for immediate relief (Hallegatte and Dumas, 2009b). Along these lines, Lackner (2018) finds evidence of highly persistent negative impacts of earthquakes on economic growth: while an average event reduces GDP per capita by 1.6% after up to 8 years, high-

[3]See Noy (2009) for a detailed review on direct damages of natural hazards.

income countries might experience some beneficial effects. On the other hand, Hsiang and Jina (2014) find much larger and statistically significant negative impacts when investigating tropical cyclones, rejecting the hypothesis that these events might stimulate growth, regardless of the income level. Nonetheless, the authors report significantly lower impacts for countries historically more exposed to tropical cyclones, thus highlighting the beneficial role of adaptation.[4]

More clear-cut results start to emerge when moving the analysis from the national to the regional level (see e.g. Xiao 2011 and Xiao and Feser 2014 on the 1993 Midwest Flood, Vu and Noy 2018 on Vietnam, Hornbeck and Keniston 2017 on the 1872 Great Boston Fire, duPont IV and Noy 2015 on the 1995 Kobe earthquake).[5] This suggests that the scale of the analysis is a crucial factor in order to spot potential signals, because of demographic dynamics (see e.g. Husby et al. 2014, Boustan et al. 2012), wealth redistribution, and governmental relief programs (De Alwis and Noy, 2019). Regional studies also highlight that impacts are highly heterogeneous, both across income classes (with poor households being more vulnerable and less able to recover) as well as economic sectors, with generally higher impacts in the agricultural (Xiao, 2011) and manufacturing one (duPont IV and Noy, 2015).

3 Standard modeling approaches

Researchers often resort to modeling approaches in order to carry out structural analysis. The two most common methodologies are Input-Output models (IOs, Section 3.1) and Computable General Equilibrium models (CGEs, Section 3.2), or some hybrid forms of the two (Section 3.3). These two approaches differ substantially in their conceptualization of the economy, and their usage crucially depends on the time horizon considered in the analysis.

3.1 Input-Output models

The IO approach aims at describing the economy through a static Leontief linear model, representing both sector-to-sector and sector-to-consumer relationships. Output in each sector is represented as input for downstream processes (Botzen et al., 2019), allowing the modeler to represent final production through a set of industry-level coefficients through which the exogenous final demand can be met (Galbusera and Giannopoulos, 2018). Thus, IOs are generally defined as demand-driven, as they typically investigate the propagation of the shock to intermediate demand inputs along the supply chain.

Short-term effects of natural hazards are often analyzed with IO-based approaches. In the short-run, the production process is in fact generally rigid and constrained by existing infrastructures and machinery. Thus, when the hazard hits, inputs start lacking, and the supply chain is immediately influenced through cascade effects. Production is affected through rigidities in inputs coefficients, rather than through price adjustments and the subsequent substitution of inputs (which are infrequently observed in such a limited time, Hallegatte (2014)). Even if prices do not adjust and input substitution is not possible, flexibility might nonetheless come in the form of imports from non-affected areas, existing inventories, or through postponement of non-urgent activities. Thus, for an IO model to be suitable, a disturbance must be long enough to produce measurable effects, but also short enough to avoid relevant substitution effects among factors (Koks et al., 2016). IOs have been applied to several

[4]See Meyer et al. (2013) for a detailed review of long-run impacts of natural hazards.

[5]See Noy et al. (2018) for a comprehensive review on regional studies.

case studies of natural disasters, including the 1995 Kobe earthquake (Okuyama, 2014), the 2006 hurricane Katrina in Louisiana USA (Hallegatte, 2008), and the 2008 Sichuan earthquake (Wu et al., 2012). IOs have been also amended by considering additional parts of the supply, e.g. by integrating a description of the water cycle (Rose, 2004b) or of the transportation network (Wen et al., 2014). Nonetheless, they are typically characterized by some structural shortcomings:

- The most simple (and early) IOs usually entail infinite elasticity of supply with respect to demand, therefore not considering supply capacity constraints. There have been attempts to create supply-driven IOs (such as the Inoperability model of Santos and Haimes 2004), though these have been criticized because they entail perfect demand elasticities with respect to supply, and perfect substitution of inputs (Oosterhaven and Bouwmeester, 2016; Oosterhaven, 2017).[6]

- Their fixed structure does not allow for input substitution, and relative price changes have no impact on the system (null elasticity of demand with respect to prices). While the costs of factor substitution are indeed often substantial, and unlikely to be made in the short-run (Crowther and Haimes, 2005), this seldom occurs after a disaster (Koks et al., 2016). Moreover, one of the core assumptions of I-O models is that any affected input will propagate its scarcity throughout the entire economy. This may be true to some degree in the very short-run but, eventually, firms will be able to find alternative suppliers. In their most basic forms, IOs further lack the possibility of substituting missing inputs through imports (Botzen et al., 2019), perhaps from non-affected areas (Hallegatte, 2008, 2014).

- There is usually no behavioural response, which in CGEs takes the basic form of price adjustments, and no adaptive capacity.

Because of the lack of these features, IO approaches tend to inflate the estimated impact of a disaster, and are often interpreted as an upper-bound.

There have been several attempts to ameliorate IOs performances, either through the addition of CGE-like features aimed at better tailoring medium-long run effects (Section 3.3), or through the inclusion of additional sectors/regions. As a matter of fact, supply chain disruptions often broaden beyond the region directly affected by the hazard. In this perspective, Okuyama et al. (1999) employ a two-regions IO model to evaluate the spatial spillovers of a localized earthquake in the rest of Japan. However, even when accounting for such effects, overestimation may nonetheless occur if the possibility of input substitution with imports from non-affected regions is not accounted for (in den Bäumen et al., 2015; Koks and Thissen, 2016). Along similar lines, Rose (2004a) argued that IOs often lack proper modeling of resiliency measures that might be put in place after a natural disaster. Rose and Wei (2013) integrate an IO model with adaptive measures such as ship rerouting, export diversion (the usage of goods that would normally be exported to substitute for lacking import goods), or putting unused capacity to work, in order to study hazard-driven disruption of seaports in Texas. Results indicate that these measures deeply influence the magnitude of the economic impacts, reducing regional impacts by 70% and national ones by 95%. Similarly, Jonkeren and Giannopoulos (2014) analyze the impact of extreme weather in Europe through an IO model including inventories, finding a 31% loss reduction due to adaptive measures.

[6] Galbusera and Giannopoulos (2018) provide a general, technical review on different IO techniques, focusing in particular on the distinction between supply- and demand-driven ones.

Finally, a generalized extension of the IO approach is represented by Social Accounting Matrix (SAM). This approach retains a static linear Leontief framework while supplementing the standard inter-sectoral information including non-corporate actors, such as institutions and households. However, there have been only a few attempts of analyzing hazard impacts with a SAM approach (see e.g. Roberts, 2000; Okuyama and Sahin, 2009; Seung, 2014).

3.2 Computable General Equilibrium models

Because of the lack of crucial mechanisms in IOs (e.g. behavioral reaction, input substitution, price changes, labor force migration), medium and long-run impacts are routinely analyzed by means of CGEs. These models are rooted in the neoclassical tradition, involving assumptions such as optimizing behavior, perfect rationality, perfect information, representative agent, and market-clearing. Their micro-foundation allows for a behavioural model of producers and consumers which respond to price signals, generally in a multi-market context (Rose, 2004a). CGEs are usually employed to assess impacts on aggregate variables (e.g. GDP as in Noy and duPont 2018), and, unlike IOs, allow for input and import substitution, thus including real-world responses to natural hazards. From a technical standpoint, substitutability is usually achieved through the usage of a Constant Elasticity of Substitution (CES) production function, instead of a Leontief specification. When the hazard hits, endogenous changes in prices and quantities temporarily alter GDP, until it gradually returns to its equilibrium level. The cumulative difference between the simulated path and the unshocked counterfactual is then interpreted as the amount of output lost due to the hazard. Quite obviously, CGEs are not well equipped to model short-run damages, where inefficient behavior and market disequilibrium are likely to be the norm rather than the exception. Shortages are more likely to propagate through rationing than through price changes (Hallegatte, 2008), which are usually not observed in the immediate aftermath of a disaster - even though price elasticity can be used as an artificial way of proxying scarcity (Hallegatte and Przyluski, 2010). On the other hand, the extreme flexibility in factor adjustment, the assumption of perfect rationality, and that of a deterministic growth path towards which the economy naturally gravitates, might lead to over-optimistic assessments of long-run losses. Thus, estimates of economic impacts of natural hazards arising from CGEs are often interpreted as a lower-bound (Okuyama, 2007).

Early CGEs initially concentrated on national scale impacts. Thanks to increasing data availability, (multi-)regional CGE are nowadays highly diffused (see e.g. Rose and Liao, 2005; Tsuchiya et al., 2007; Carrera et al., 2015). In order to exploit the increasing availability of highly granular data, scholars have embarked into ever finer versions of CGEs, thereby including e.g. fine-grained data on land use or transportation structure (Anas and Liu, 2007; Tsuchiya et al., 2007), or ameliorated catastrophe models - see e.g. Pauw et al. (2011) for the inclusion of a hydro-meteorological crop loss model with a regional CGE model. More recently, Spatial CGEs (SCGEs) introduced a spatially explicit treatment of impacts in order to study their geographical distribution, allowing for intra- and inter-regional trading - e.g. transportation networks as in Tatano and Tsuchiya (2008), or household mobility as in Giesecke and Madden (2013). Another strand of the literature has focused on the role of resiliency measures, broadly intended as the adaptive capacity of the system. Investigating the disruption of the water system following an earthquake in the Portland area, Rose and Liao (2005) allow for adaptive responses by means of dynamically re-calibrating - through survey data - the parameters of a production function with water as an input. Results show that not accounting for such resilient behaviour would magnify indirect losses, from 20% to 90% of direct losses. This confirms the relevance of behavioral adjustments and is in line with other studies indicating smaller ratios between indirect and direct losses in CGEs compared to those in IOs (Rose et al., 2016). Finally, Integrated Assessment Models (IAMs), just like CGEs, are based on the general equilibrium apparatus. They couple a modeled carbon cycle with a CGE-like macroeconomic model, and a damage function linked with climate-related sufficient statistics, usually global temperature anomalies (Stanton et al., 2009; Stern, 2013; Parson and Fisher-Vanden, 1997). Although these models are generally concerned with the overall impacts of climate change, there are cases of applications of IAMs to the study of specific natural disasters (e.g. Narita et al. 2010; Diaz and Keller 2016).

As pointed out in Section 1, the micro-foundations of CGEs have been often criticized, mainly on the grounds of the unrealism of the assumptions upon which they are built on. The paradigm of the rational agent is indeed in stark contrast with empirical evidence on how individuals behave in risky situations, especially when dealing with low probability/high impact events such as natural disasters (Kahneman and Tversky, 2013; Aerts et al., 2018; Safarzyńska et al., 2013; Schrieks et al., 2021). Ruling out interactions, by assuming that a multitude of interacting, heterogeneous agents can be adequately described by a single agent, also poses theoretical issues which may impair the proper modeling of hazard impacts. Individual and social learning can substantially influence the adoption of protective measures (Shogren and Crocker, 1991), as well as affect the diffusion of information in times of deep uncertainty (Safarzyńska et al., 2013). Both learning mechanisms are also relevant to investment decisions in hedging against natural hazards (Siegrist and Gutscher, 2008). Moreover, collective phenomena such as migration or evacuation are often not strictly due to economic reasons but have an important sociological component (Entwisle et al., 2016).[7] Interactions are particularly relevant for firms, which are generally interacting within networks of production, and specific failures can lead to 'cascading effects' throughout the economy (Safarzyńska et al., 2013). The relevance of the network structure is well known to scholars, and it is indeed partially taken into account within the IO framework. For instance, Henriet et al. (2012) developed a regional economy model based on the ARIO informed with disaggregated sector-scale IO tables, showing output losses to be related to both heterogeneities in direct effects, as well as to the production network structure.[8] Failing to account for these effects may lead to a severe misestimation of natural hazard risk. Perhaps, the most limiting assumption is that of equilibrium. By postulating a return towards a deterministic growth path, CGEs are effectively assuming that such large-scale events do not alter the trajectory of the economy, but only temporarily diverge it.[9] While the notion of equilibrium has been largely contested by economists along with the evolutionary tradition (see e.g. Fagiolo and Roventini, 2016), these criticisms are particularly relevant for such rare events. As noted in Section 2, growing evidence is pointing to the existence of permanent effects, as well as hazard-induced poverty traps. In some cases, the economic disruption is so violent to lead to institutional changes and even political revolutions (Cavallo et al., 2013). Additionally, trade-offs arising from capital destruction (R&D activities *vis-à-vis* replacement, Safarzyńska et al. 2013) may induce firms in a specific region to embark on different technological trajectories (Dosi, 1982), thereby permanently changing the structure of the economy.

[7] For instance, Riad et al. (1999) show that social influence, together with risk perception and access to resources, is among the main factors affecting the decision about whether to evacuate or not in case of natural hazard, thus likely to impact the number of casualties.

[8] Output losses may be indeed greater if all firms are concentrated in the same location, thus linking the production network topology to the potential economic losses due to disruptions.

[9] In theory, one could have models with multiple equilibria, although these are seldom implemented in practice.

3.3 Hybrid models

Because of their distinct - and to a certain extent opposite - features, there have been notable attempts to devise hybrid models that incorporate elements from both CGE and IO approaches. Some of these models attempt at introducing more realistic representations of the production process into a CGE backbone, thus including reduced substitution elasticities (e.g. Rose et al. 2007) or Leontief production functions in intermediate inputs (e.g. Horridge et al. 2005). Another approach consists in augmenting an IO framework with CGE features, such as price reactions (Hallegatte, 2008, 2014). The Adaptive Regional Input-Output (ARIO, Hallegatte, 2008) is one of the most renowned examples of hybrid models. ARIO accounts for production constraints, and features several adaptation mechanisms. Firms are allowed to overproduce in order to counterbalance input shortages, thus effectively taking into account both supply and demand channels. It further includes price flexibility - with prices increasing linearly when underproduction occurs - as well as imports and exports across affected regions. Remarkably, the model appears to be highly sensitive to the parameters governing the behavioral rules. Koks et al. (2015) further extend ARIO, including input substitution. The authors employ Cobb-Douglas production functions, calibrated through IO tables, to estimate the effects on production of both reduced capital and labor supply after a flood. The Multi-Regional Impact Assessment model (MRIA) by Koks and Thissen (2016) focuses more specifically on modeling suppliers' input substitution from outside the affected region, through the application of nonlinear programming to account for endogenous trade links (calibrated on real multi-regional trade exchanges) and supply constraints. It also shares several features of ARIO, and accounts for inter-regional trade flows. Even if input substitution is not accounted for, resilience emerges through flexible movements of production processes across regions. Results point to an increase in economic activity in non-affected regions - coupled with reduced indirect losses in affected ones - thus substantially lowering the aggregated impact.

Although these hybrid models generally aim at finding a balance between the CGE and IO approaches, their outcomes may still differ substantially. Koks et al. (2016) conducted a systematic comparison between different assessment methodologies, focusing on flooding scenarios of the Italian river Po. Using the same input data, they compared economic losses as predicted by three different models: the ARIO by Hallegatte (2008), the MRIA by Koks and Thissen (2016), and a regional version of the CGE model already employed by Carrera et al. (2015) to study the 2000 Po river flood. Though losses in the impacted region are rather similar across the three methodologies, they varied by a factor up to 7 in non-affected parts of the country. More specifically, differences between losses in MRIA and the CGE model were relatively small compared to those in ARIO, which provided much more negative estimates. As pointed out by Koks et al. (2016), this is largely due to the linear structure of ARIO, which does not allow for substitution of imports from non-affected regions.

Lastly, a distinct type of hybrid approach consists of coupling either a CGE or an IO model with physical sub-models, in order to improve their accuracy. Pauw et al. (2011) combined a CGE model with a hydrologic sub-model for drought and floods in Malawi, while (Carrera et al., 2015) adopted the same strategy to analyze the 2000 floods of the Italian river Po. Since infrastructure systems - especially those related to transport - might substantially catalyze - or reduce - disruptions, Tsuchiya et al. (2007) augmented their spatial CGE model with a transportation sub-model of freight and passengers, to investigate cascade losses related to earthquakes in Japan. Finally, the TransNIEMO model by Cho et al. (2015) uses a multi-regional IO model together with a modeled US national highway system to study resilience to hazard-driven disruptions, with a focus on bridge collapses and tunnels closures.

3.4 Production networks

A network representation allows studying how relationships and interactions between sectors and firms may propagate localized shocks, giving rise to non-trivial aggregate macro effects (Hallegatte, 2019). The relevance of such linkages in the context of disaster impacts has encouraged scholars to embed insights from the network literature into their models.

In this framework, we can identify two main approaches. The first comes from a complexity perspective, and generally combines an ABM core with insights from the complex networks literature. As well exemplified by ABM investigating financial instability and macro-prudential policies (see e.g. Bardoscia et al., 2017), complex linkages can be quite readily implemented in an ABM framework, given the built-in heterogeneity among agents. Works in this direction include the seminal one by Henriet et al. (2012), as well as the more recent one by Inoue and Todo (2019) (see Section 4), both based on the ARIO model (Hallegatte, 2008). The second approach consists of the usage of fully-fledged General Equilibrium models, augmented with a representation of the production network. The theoretical underpinnings of this approach come from the literature on the propagation of micro-level shocks through intra-firm linkages (Gabaix, 2011; Carvalho et al., 2021; Acemoglu et al., 2012; Baqaee and Farhi, 2020). As in the General Equilibrium tradition, interactions between different units (firms, but more often industries) rely on price adjustments, arising in turn from optimizing behaviour, while shocks propagate through the network of input-output or customer-buyer relationships.

Despite the wide range of theoretical works, empirical efforts to study the economic impacts of natural disasters within this approach have been rather scant, mainly due to the requirement of highly granular data, which are often unavailable or proprietary. A remarkable exception is constituted by the work of Barrot and Sauvagnat (2016), who find substantial losses on customers whose suppliers were affected by natural disasters in the US, especially when the latter are highly specialized. Boehm et al. (2019) studied instead the propagation of the 2011 Japanese earthquake impacts to US affiliates. Finally, the recent work by Carvalho et al. (2021) employs a theoretical framework based on Acemoglu et al. (2012) to document the propagation of shocks through firm-to-firm linkages for the same earthquake, exploiting an extensive dataset on Japanese firm-to-firm relationships.

4 Agent-Based Models

Agent-Based Models (ABMs) are particularly well-suited to model complex systems. In principle, they allow for a detailed representation of sectoral heterogeneity and interdependence just like IOs, coupled with a model structure of the economy that allows for long-run analysis, without recurring to the strict assumptions typical of CGEs (e.g. representative agent and market clearing). Their bottom-up approach and modular structure allow modelers to carefully specify micro-level behavioral rules and network connections. Agents' behavior is derived from observed empirical regularities and often comes in the form of simplified decision rules and heuristics, thus allowing for a more realistic representation with respect to both IOs and CGEs. Through adaptive learning and feedback mechanisms, behavior and network structures can evolve endogenously, along with an ever-changing economic environment.

A substantial number of authors have concentrated on the usage of ABMs to better describe interactions and feedback loops among socio-economic systems and the natural environment, without explicitly focusing on the impacts of natural hazards.[10] Along these lines, Lamperti et al. (2018a) developed the first fully-fledged agent-based IAM, focusing on feedbacks between climate dynamics and the economic system. ABMs have also been applied to the study of water management and resource-sharing mechanisms (Tesfatsion et al., 2017), agriculture and land use (Coronese et al., 2021; Parker et al., 2003; Schreinemachers and Berger, 2011; Berger and Troost, 2014; Troost and Berger, 2015), climate-induced migration patterns (Angus et al., 2009; Kniveton et al., 2011), adaptation to climate variability (Hailegiorgis et al., 2018) and climate-energy nexus (Castro et al., 2020). While the role of extreme events in these works is often limited or absent, they put forward key concepts about the co-modeling of human systems and natural ones. Such nexus is indeed increasingly recognized as complex, with feedback loops along both directions.

In what follows, we review existing ABMs explicitly devised to analyze natural disaster risk and/or impacts. Because different - and sometimes conflicting - formal definitions ABMs can be found in the literature, [11] we here concentrate on ABMs which define themselves as such.

4.1 Risk assessment

Hazard risk-assessment is an area of research where ABMs have been fruitfully employed. The goodness of a risk-assessment exercise is intimately intertwined with the accuracy of its behavioral representations. The severity of assets' exposure and ensuing losses are indeed strictly related to actions undertaken by individuals, including investment in mitigating and adaptive capabilities, their degree of awareness, and purchase of hazard-related insurance policies (e.g. for floods and droughts, Kreibich et al. 2011). These actions are likely to be undertaken in ways that are not accurately represented by Expected Utility Theory (Aerts et al., 2018; Aerts, 2020; Schrieks et al., 2021). In this perspective, ABM offers a suitable framework for appropriately modeling human behavior, possibly leading to an ameliorated risk-assessment.

Haer et al. (2017) use an ABM to investigate efforts in loss-reducing investments related to flood risk. Focusing on the case of the Heijiplatt neighbourhood in Rotterdam, they simulate climate-change-induced physical flood risk and how it interacts with the implementation of protective measures and the purchase of flood insurance schemes. Investment decisions are carried out under three behavioural specifications: i) Expected Utility Theory, ii) bounded rationality (as in prospect theory, Kahneman and Tversky 2013), and iii) a Bayesian-update version of prospect theory. Results highlight a reduction in risk by a factor of two when individual dynamic adaptation is considered. Remarkably, such reduction appears to be more marked when agents are employing heuristics instead of rational expectations. Similarly, Coates et al. (2019) employ an ABM to study the effectiveness of flood risk adaptation efforts in UK manufacturing SMEs. Filatova et al. (2011a) employ survey data to calibrate an ABM of the land market, studying the impact of flood risk perception on the evolution of land use in coastal areas of the Netherlands. The authors show that accounting for a right-skewed distribution of risk perception - *in lieu* of the representative agent assumption - generates a much more marked development in riskier areas (and thus higher potential losses), showcasing the ability of ABM models to replicate stylized facts (Noy, 2009) by exploiting their built-in heterogeneity. The presence of governmental protection measures can also reduce the incentive for individual adaptation, and result in riskier behavior, including relocations to more exposed areas. Haer et al. (2020) investigate this "paradox of floods" at the

[10]See Balint et al. (2017) and Lamperti et al. (2019) for reviews on the topic from a complexity perspective.

[11]For a detailed discussion, we point to Tesfatsion and Judd (2006), or to discussions in Pyka and Fagiolo (2007) and LeBaron and Tesfatsion (2008).

European level using an ABM approach, confirming that proactive governmental measures may lead to lower physical risk but higher impacts, due to moral-hazard. This result echoes the "target shrinking" strategy advocated by Perrow (2011), who advised the United States to concentrate on reducing the exposed population in more vulnerable coastal areas, rather than focusing on ex-post assistance that might generate adverse effects. More akin to the economic geography literature, Taberna et al. (2021) propose an ABM along with the evolutionary economics tradition, inspired by the K+S macroeconomic ABM family (Dosi et al., 2010). The model is employed to study the interplay between the geographical distribution and agglomeration of productive units and flood hazards. Concerned with the endogenous migration decisions of firms and households, as well as technological learning catalyzed by geographic proximity, the model is able to replicate some key stylized facts of the economy and provide insights into realistic future scenarios of hazard risk. Overall, despite the limited number of works, scholars are increasingly looking at ABMs as a useful tool for risk-assessment - see the detailed reviews in Taberna et al. (2020) and Aerts (2020) for floods, Schrieks et al. (2021) for droughts, and (Filatova et al., 2011b) for climate-risk perception in land markets.

4.2 Impact assessment

Similarly, a growing number of authors is employing ABMs for hazard impact assessment, as an alternative to CGEs and IOs. In addition to the reasons which make ABMs suitable for hazard risk-assessment (built-in heterogeneity and more realistic behavioral responses), they also allow for non-trivial interactions among agents, and typically do not resort to equilibrium assumptions. As argued in Chapter 1, both characteristics are highly desirable for a correct modeling of the aftermath of a natural disaster - which is, almost by definition, an extraordinary event. This strand of literature is still in its infancy, and existing models vary in scope, level of aggregation and of abstraction, as summarized in Table 1.

Colon et al. (2021) and Otto et al. (2017) represent two examples of ABMs aimed at analysing channels of propagation of localized shocks to the supply-chain network. Otto et al. (2017) propose a novel, global, daily-resolution ABM model, labeled Acclimate, where agents are represented by national sector industries and consumers, embedded in a network structure of production and international trade. Sectorial weights are calibrated through IO tables, while agents form expectations on future levels of demand and maximize their objective functions accordingly. As such, the model shares some features which are typical of CGE approaches. Results confirm that buffers such as warehousing and idle capacity are able to substantially mitigate both local indirect effects of natural shocks, as well as their propagation along globally interconnected value-chains. Similar results on the role of inventories are obtained by Colon et al. (2021), who propose an extended version of the model presented by Henriet et al. (2012), further including a firm-level network structure and a model-representation of the transportation system in Tanzania. Their idealized shocks generate a highly non-linear relationship between the duration of the disruption and the magnitude of indirect losses, very much in line with what is usually observed after natural hazards globally (Hallegatte, 2015). Along the same lines, Inoue and Todo (2019) use an ABM based on Hallegatte (2008) and Henriet et al. (2012), informed with very granular Japanese firm-level data on customer-buyer relationships, to study the indirect effects of the 2011 Great East Japan earthquake. Poledna et al. (2018) use instead a macroeconomic ABM of Austria coupled with a probabilistic damage function to evaluate the overall sign of the indirect impacts of floods, finding mixed evidence.

Model	Aim	Case study	Features	Main findings
SHEL (Naqvi and Rehm, 2014a)	Macroeconomic effects of natural disasters for low-income countries	Floods in Pakistan	Stock-Flow Consistent ABM	- Low income group more vulnerable (especially to starvation) and less likely to be back at pre-disaster levels. - Positive impact of policy experiment: food and cash transfer schemes.
Acclimate (Otto et al., 2017)	Propagation of supply network shocks in the global economy	Shutdown of Japanese manufacturing; global economic effects of floods (Willner et al., 2018)	Extensions of an agentified IO model with elements of flexibility of CGEs	- Mitigation of indirect effects through warehousing and idle capacities. - Willner et al. (2018): without structural adaptation, increased flood losses by 20%.
Poledna et al. (2018)	Sign of economic impacts	Floods in Austria	Macroeconomic ABM (Poledna et al., 2020) with probabilistic damage function	- Moderate disasters have small but positive effects in the short-medium term, negative in the long-term. - Large disasters have negative impact in immediate aftermath but temporarily positive in the short-medium term.
Inoue and Todo (2019)	Propagation of shocks in a real national production network	Earthquake in Japan	Firm-to-firm supply chain network in an ABM based on Henriet et al. (2012) and Hallegatte (2008)	- Large impact of indirect effects. - Importance of the (real) network of the production system. - Ability to substitute inputs fundamental for the resiliency of the system.
Colon et al. (2021)	Resilience of supply-chain network and transportation system	Transportation and supply-chain failures in Tanzania	Firm-to-firm supply chain network coupled with transportation system (built up on Henriet et al. 2012)	- Resiliency measure should aim at strengthening transportation system, better inventory and buffers management. - Longer repairs increase indirect losses nonlinearly.
Ghaffarian et al. (2021)	Physical recovery after Typhoon	Haiyan Typhoon in Philipinnes	Estimates of reconstructions from remote sensing images	- Supporting employment has limited effects in all areas. - Relocation of destroyed sites helps recovery in informal areas.

Table 1: Selected ABMs for natural hazard impact assessment.

Because of the high diversity of observed patterns across income classes, Naqvi and Rehm (2014a) and Naqvi and Rehm (2014b) propose a novel ABM labeled SHEL, specifically designed for low-income countries, for which micro-data is often scarce or unavailable. The main focus of the model is to analyze the distributional impacts on income and consumption for Punjab, a region that flooded in 2010. It comprises two types of agents (workers and owners), producing two types of goods (a consumption and a tradable one), in two regions (urban and rural areas). A probabilistic decision-making process (composed of six distinct modules) governs the evolution of aggregate income and consumption levels. The model is then calibrated using aggregate data for the Punjab area and runs with a daily resolution. Their findings depict highly unequally distributed impacts, with bottom-earners suffering the most, both in terms of immediate starvation and in terms of time to recovery to pre-shock income levels. Notably, the model is stock-flow consistent, and it is used as a testbed for several demand-side policy interventions (e.g. cash transfers). Naqvi (2017) applied the same framework to study the 2005 earthquake in the northern part of Pakistan, informing the model with detailed spatial data. Naqvi and Monasterolo (2021) propose instead a theoretical framework to study the effects of climate shocks on food production in an agriculturally-dependent, low-income country. The model couples a multi-layered network representation of supply-chain together with a heterogeneous, behaviorally characterized household side, whose decision-making process (e.g. about migration and trade choices) is crucially shaped by agents' interaction. Ghaffarian et al. (2021) develop an ABM to study resiliency and recovery following the Haiyan Typhoon in the Philippines in 2013. Detailed modeling of physical recovery using remote sensing images is coupled with behavioral equations governing agent decisions. The authors experiment with two distinct policy exercises, namely introducing employment support, and incentives to the reconstruction of sites, tracking the economic recovery[12] for residents, in both formal and informal (slums) urban areas. Their findings indicate that relocation of sites accelerates recovery in informal areas, while employment support policies have little effect on the velocity of re-

[12] Recovery is quantified in terms of utility levels.

covery in both groups. Finally, Kanno et al. (2019) propose an ABM to study interdependencies in urban systems among industrial production, civil life, and lifeline infrastructures during post-disaster recovery.

4.3 Mixing ABMs and CGEs

Some scholars have embarked on work aimed at integrating insights and characteristics from ABMs into CGE structures[13], in the attempt to equip the latter with more realistic micro-foundations (Botzen et al., 2019; Krook-Riekkola et al., 2017). One existing approach departs from a CGE core, and then allow for features such as heterogeneity and social interactions, generally through disaggregation of the representative agent (Niamir et al., 2020; Rausch et al., 2011). For instance, Duarte et al. (2016) employs a regional CGE model to investigate the impact of improving environmental awareness in Spain, exploiting survey data to calibrate habits, consumption patterns, and households' sensitivity to various environmental behaviors. While the usage of survey data ameliorates the representation of heterogeneity, agents' choices remain fixed over time and are still taken under conditions of perfect information, thus neglecting any representation of behavioral changes, bounded-rationality, and social interactions (Niamir et al., 2020).

From a purely theoretical perspective, there are several methodologies aimed at combining independently developed top-down (e.g. a CGE) and bottom-up models (e.g. ABMs or micro-simulation models).[14] Three types of "linking" are usually envisioned (Böhringer and Rutherford, 2008):

- The "soft-linking" approach connects a top-down model with a bottom-up one by using outputs of one model as inputs for the other. This method often leads to internal coherence problems, due to the different behavioural assumptions of each module (Husby, 2016).
- The "hard-linking" approach imposes the output of the bottom-up model to be part of the solution of the top-down one.[15] This methodology has however severe limitations, due to difficulties in convergence in CGE/IO modules.
- A third intermediate approach aims at maintaining the CGE structure while letting its parameters to be determined by a reduced form model (see e.g. Bosetti et al., 2006).

In the context of hazard impacts assessment, the few works aiming at integrating ABMs and CGEs use a soft-linking approach. Among them, Husby (2016) employs an ABM of opinion dynamics to analyze the impact of public concern on disaster losses as predicted by a Spatial CGE model. More recently, Niamir et al. (2018) investigate the macroeconomic effects of changes in individual behaviour and social norms - and their interaction - on climate-change mitigation policies, using an ABM of the family of BENCH models [16] , originally developed to study energy use.

Finally, other authors have proposed alternative integration strategies, although with a high level of abstraction. Among them, Safarzyńska et al. (2013) put forward an integration method to accommodate insights typical of the evolutionary tradition into a more standard (CGE/IO) framework, while Smajgl et al. (2009) propose a farm-level conceptual integration of ABMs and CGEs for fishery policy assessment.

[13]In principle this applies to IOs as well, although to the best of our knowledge there are no works in this direction.
[14]See Richiardi and Richardson (2017) for a detailed discussion. See also Rausch et al. (2011) and Niamir et al. (2020).
[15]Böhringer and Rutherford (2008) provide the most detailed example of this methodology.
[16]See Niamir et al. (2020) for a more recent application.

5 Towards a complexity-based approach: challenges and ways forward

In this paper, we critically reviewed the state of the art in the modeling of environment-economic systems, focusing in particular on the analysis of natural disaster impacts. Conventional approaches are generally based either on Input-Output techniques, on Computable General Equilibrium models, or on some mixture of the two. Both methods, depending on the end-use, can deliver informative estimates, and have undoubtedly advanced our understanding of the composite mechanisms at work in the aftermath of a catastrophic event. Nonetheless, they suffer from intrinsic drawbacks which limit their ability to fully grasp the complexity of such dynamics. In a nutshell, they boil down to a scant representation of heterogeneity and interactions, an unrealistic description of behavioral rules governing agents' actions, and a deterministic view of the evolution of the economic system. Because of such drawbacks, dominant approaches are likely to lead to either over-optimistic - as in CGEs - or over-pessimistic - as in IOs - assessments of hazard risk and related impacts.

Here we have argued that Agent-Based Models represent a powerful tool to ameliorate the modeling of long-run consequences of natural disasters, and - along with existing approaches - help in the assessment of hazard risk. Indeed, a complexity-based approach can shed light on critical mechanisms, which are often overlooked by standard modeling techniques. As extreme events are likely to become more frequent and severe, due to anthropogenic climate change, a thorough understanding of their impacts is crucial in order to design appropriate policies. ABMs can in fact serve as laboratories for artificial counterfactuals and test-beds for synthetic adaptation and mitigation policy experiments, so to investigate the evolution of risks and impacts across distinct socio-economic and climate scenarios.

A critical point to our argument is that complexity-based methods, and ABMs in particular, are immune by construction to the criticisms listed above. While this is true in principle, they do suffer from some limitations in practice. The most obvious is perhaps the presence of several degrees of freedom in modeling choices, both in terms of structural relationships as well as of behavioral rules. This lack of unified grammar is likely one of the main reasons that have led researchers to embark in the development of hybrid models, in the attempt to integrate sound, empirically driven micro-foundations - typical of ABMs - while maintaining a CGE structure - capable of granting internal coherence and comparability across models. This avenue of research is certainly promising and can produce models with an ameliorated representation of heterogeneity. Nonetheless, it still relies on a theoretical apparatus which is based on equilibrium assumptions, and where the impact of non-trivial interactions at the meso- and macro-level is structurally circumscribed.

The literature on ABMs applied to disaster risk and impact assessments is still in a nascent state. Overall, we believe that the ABMs showcased in Section 4 constitute examples of a promising methodology. In this spirit, we identify some critical issues which are at the forefront of research both in agent-based modeling and in hazard impacts analysis, and constitute crucial avenues of future developments for ABMs to become a prominent and well-established modeling approach to the issues discussed here.

- *Calibration and validation*: The flexibility of ABMs often comes at the expense of their tractability. Tractability rapidly deteriorates along with the scale (e.g. geographical) and the scope (e.g. types of hazards, policy toolkit) of the analysis. This often translates into difficult calibration exercises, especially when dealing with ex-ante policy assessments. The literature on ABMs calibration and validation is nonetheless gaining rapid momentum and has already obtained promising results (Fagiolo et al., 2019; Lamperti et al., 2018b).

- *Data availability*: The ability of ABMs to accurately replicate real-world-like heterogeneity and interactions crucially relies on the availability of realistic data to calibrate models with Hallegatte (2019). The lack of granular data is particularly pronounced in developing countries, which are projected to suffer the largest impacts from climate change. Thanks to the recent availability of supply-chain micro data, works such as Inoue and Todo (2019), Ghaffarian et al. (2021), and Colon et al. (2021) have shown how a more fine-grained representation of the production structure is fundamental for a better understanding of the economic impacts of natural disasters.

- *Stock-flow consistency*: Stock-Flow-Consistency (SFC) is a generic property of a model, and is not directly related to the issue of modeling hazard impacts. SFC refers to the rigorous treatment of all flows and stocks in the economy. Through a matrix representation, the modeler ensures a coherent treatment of all inflows and outflows in the economy, which accrue or decrease the associated stocks. By the same token, SFC is not a distinctive feature of ABMs. While there is a long history of SFC modeling in the Post-Keynesian tradition (see e.g. Caverzasi and Godin 2015), any modeling strategy which has enough built-in heterogeneity across agents can adopt it. Indeed, there have been numerous SFC-ABMs developed in the context of financial regulation and macro-prudential policies (see e.g. Seppecher 2012; Teglio et al. 2012). However, this approach is still the exception, rather than the norm, in ABM modeling of natural disaster impacts. A systematic treatment of stock and flows is a key prerequisite for ABMs to achieve a degree of internal coherence which allows for scaling-up along different dimensions (e.g geographical, sectorial). Most importantly, SFC becoming a standard feature of ABMs would represent a major stepping stone in terms of comparability across models.

- *Channels of transmission*: The general lack of understanding of micro-level channels of adaptation is a crucial limiting factor in impact assessment. As underlined by Schrieks et al. (2021), the endogenous dynamics of behavioural responses are still not entirely understood, together with their repercussion on consumption and population patterns. In this perspective, ABMs constitute a natural candidate to explore the emergence of macro-level properties of the system. Nonetheless, micro-behavior should be carefully designed in order to reflect empirical evidence. Failing to take these aspects into account can lead to a distorted representation of natural hazard impacts (especially in migration patterns and in the housing market), and in turn to poor policy responses (Naqvi and Rehm, 2014a).

- *Demand effects*: Even if routinely analyzed with demand-based approaches (such as IOs), shocks from natural hazards have a large supply-side component (Hallegatte et al., 2011). Demand effects are thus often overlooked. Nonetheless, demand-side responses can be remarkable in case of extreme events, characterized by e.g. market failures, inefficient income stabilizers, and incomplete insurance markets. These channels are especially relevant if income inequality, heterogeneous adaptive capacity, and resilience are taken into account. In this perspective, ABMs offer a powerful platform to embark e.g. Keynesian features in the analysis (see e.g. Dosi et al. 2010).

- *Demand and supply interplay*: Because natural disasters affect both the supply and the demand side of the economy, their interplay can generate non-trivial dynamics. Shocks to both were indeed one of the peculiarities of the COVID-19 pandemic recession. Recently, Pichler and Farmer (2021) and Reissl et al. (2022) have stressed the relevance of their joint interaction in an IO framework, as well as the importance of a network representation of industries, which might propagate shocks further. In this spirit, we echo Pichler and Farmer (2021), who underline the necessity to fully incorporate these dynamics in the analysis of natural disaster impacts.

- *Spatial structure*: Natural disasters, by their own nature, have a well-defined spatial structure. Because different signals in impacts appear at distinct scales of aggregation, spatial inter-dependencies are highly relevant, as they help understand channels of transmission from the micro-level to the meso and macro scales. Driven by the spur in the availability of high-resolution, geo-localized data, ABMs can be easily endowed with a spatial structure that embeds geographical inter-dependencies, in addition to economic ones (as in e.g. Naqvi 2017). Another approach (as pioneered by Ghaffarian et al. 2021) is to use increasingly available remote-sensing data to accurately calibrate or validate non-explicitly spatial ABMs.

Acknowlegments

Matteo Coronese acknowledges the financial support from the Economics of Energy Innovation and System Transition (EEIST) Project. We thank Francesco Lamperti, Marco Pangallo, and Beatrice Negro for their valuable comments and hints.

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