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YSSP Report
Young Scientists Summer Program

Propagation of disaster shocks through supply-chain networks under incomplete information

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Approved by

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Abstract

Increasingly complex linkages of the global economy can be a channel for the propagation of negative climate-related shocks with the potential to deteriorate resilience and sustainability in societies. Given projected increases in disaster risks due to climate change, developing models that more accurately simulate the propagation of shocks through economic networks becomes crucial for designing effective prevention and recovery strategies. This study focuses on the short-term decision-making process of economic agents in disaster aftermath and its implications for the propagation of disaster shocks. We develop a new recursive dynamic model, in which a key feature of economic agents' behavior in disaster aftermath, making decisions with incomplete information, is introduced. We apply the model to study the propagation of economic impacts induced by stylized disasters and find that it can reproduce the theoretically expected decision-making process of economic agents under incomplete information in a rapidly changing economic environment. Besides the disruption of intermediate materials supply, it captures another important channel that causes indirect losses, i.e., the lack of information. On top of a more comprehensive risk assessment, the proposed approach provides a modeling framework for analyzing the relation between information and disaster propagation.

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1. Introduction

Natural disasters are one of the major risks faced by human societies and economic systems. With the increasingly complex supply-chain network of the global economy, the impact of natural disasters is not limited to direct damages to the human population and physical assets, they also disrupt the functioning of the overarching economic system, leading to additional losses through supply-chains, often referred to as indirect losses[1,2]. Evidence from studies on past natural disasters shows that indirect effects can represent a significant, or even dominant, share of total losses[3,4]. Given projected increases in disaster risk due to climate change[5] and increases in complexity of the global supply chains[6], a comprehensive understanding of the propagation of economic disaster shocks will be increasingly important for developing effective prevention and recovery strategies.

Many methods have been proposed to analyze the propagation of negative shocks through economic networks in the existing literature, which can be mainly categorized into two strands. The first category comprises the models based on Input-Output (IO) analysis. A standard IO model can be described as a static linear model that presents the economy through sets of fixed relationships between sectors themselves (the producers) and others (the consumers)[7]. Therefore, IO models can capture the ripple effect triggered by supply constraints in the economic networks in a very straightforward way[8,9], which makes it one of the most applied models to assess the indirect economic impacts of disasters[2,10,11].

The second type of model widely used in disaster impact assessment is Computable General Equilibrium (CGE) based models. A neoclassical CGE model is a system of equations that describes the behavior of firms and households and their interactions by functional relationships subject to prices and market clearing conditions[12]. Compared with IO models, CGE models consider the strategic behaviors of economic agents under the profit and utility maximization assumptions. CGE models, therefore, can better capture the adaptive response of economic agents to shocks[2]. However, due to their relative-prices adjustment mechanism, CGE models tend to be overly optimistic about market flexibility in short-term disaster aftermath[2,8]. Hence, IO models, with their more rigid structure, are often considered more suitable for short-term indirect disaster risk assessments, while CGE models are often considered more suitable for studies focus on long-term effects[1,3,8,9,13].

While the exiting research and studies, e.g. those mentioned above, have done a lot of work in applying economic models to the field of indirect disaster impact assessment, the modeling of the decision-making process of economic agents in disaster aftermath remains rather preliminary. The aftermaths of a disaster are marked by shortages and excesses, price heterogeneities, lack of information, over or under-reactions, etc. CGE models fail to capture these behaviors, because they posit that the economy remains at an equilibrium state. Information is ubiquitous and all quantities adjust instantaneously such that supply and demand remain equal. Some studies have tried to analyze economic dynamics out-of-equilibrium under the general equilibrium framework[14-16] or agent-based approach[17,18].

IO models offer a more flexible framework to simulate such out-of-equilibrium dynamics. But their representation of economic agents is extremely simplistic, such that multiple ad-hoc mechanistic rules need to be added to simulate how agents make decisions. These rules may be reasonable in certain situations, but not in others. For example, when modeling the distribution of inadequate resources in disaster aftermath, Hallegatte[1,3] employ a rationing scheme in which business-to-business linkages are prioritized and the remaining resources are distributed to other agents in proportion of their demand. Instead, Zeng et al (2019)[19] argue that priority should be given to human "basic demand" for severe disasters to make a more realistic representation. These specific rules limit the validity of such models and lead to challenges for general applications.

Another limitation of both approaches is the assumption of ubiquitous information, which is often implicit. Information is critical during a disaster aftermath, because it is often distorted (e.g., rumors) or missing (e.g., communication network breakdown). In global and complex supply chain networks, information does not flow well even in the absence of shocks, which has concrete consequences, for instance on price formation (bullwhip effect).

To fill both gaps, we propose an IO-based model with a CGE-inspired agent behavior and an explicit modeling of information limitation. We introduce a local optimization principle to govern all relevant decisions of economic agents, e.g., firms decide on their production level by profit optimization and households distribute their income to commodity consumption and saving based on utility maximization. Agents choose their strategies according to their own situation and the expected situation of other agents. The local optimization principle, therefore, characterizes the strategic behaviors of agents in disaster aftermath, but not require all agents to reach a coordinated optimization situation simultaneously as in CGE models. The out-of-equilibrium dynamics in disaster aftermath are endogenously derived from the non-coordinated strategies of agents. Meanwhile, this modeling framework makes it easy for us to analyze the impact of information on disaster propagation. When agents form expectations of other agents' situations and actions, we can very flexibly assume how much information it holds and check how this affects the dynamics of the system.

We apply the model to study the propagation of economic impacts induced by stylized disaster shocks. We find that model results qualitatively reproduce the theoretically expected economic dynamics in a post-disaster phase. Also, it can capture the theoretically expected decision-making processes of economic agents in a situation of incomplete information in a rapidly changing economic environment.

This report contributes to the research on disaster impact assessment tools. It goes beyond the current state of the literature by developing a model that is better able to represent the mechanism of the propagation of disaster shocks in supply-chain networks, by taking a closer look at the decision-making process of economic agents in disaster aftermath. Agents' behavior is modeled according to one general assumption—namely, the local optimization principle—instead of multiple reasonable ad-hoc rules from experience. This approach avoids arbitrary rule-setting and thus provides a broader range of application. More importantly, we introduce the assumption of incomplete information, which is more realistic for economic agents in disaster aftermath than assuming perfect information. This extension not only allows us to capture the theoretically expected decision-making process of economic agents in settings of incomplete information, but also opens up the possibility to analyze the relation between information and disaster propagation.

The report proceeds as follows. Section 2 reviews the relevant literature and discuss in how far our model differs from existing approaches. Section 3 describes the new proposed recursive dynamic model for assessing short-term indirect effects of natural disasters. Section 4 illustrates the model by assessing a hypothetical example of stylized disaster shocks. Finally, Section 5 summarizes our findings, highlights the pros and cons of the proposed modeling approach, and proposes insights for further research.

2. Literature review

Input-Output (IO) models and computable general equilibrium (CGE) models are the most popular approaches in disaster-induced economic risk analysis. IO is an effective tool to capture inter-linkages of sectors/industries within an economic system, and to represent economic relationships between providers and consumers. With consideration of bottlenecks on the of supply-side, IO is able to measure the impact of input scarcity on the final outputs through economic supply chains

(Oosterhaven, 1988)[20]. Many scholars have contributed to the measurement of disaster impacts through using IO model. Cochrane (1974)[21] is one of the earliest studies to assess the influence of natural disasters by constructing an inter-industry model based on IO theory. Then, the Inoperability Input-Output Model (IIM) was constructed to measure the ripple economic losses caused by immediate shocks to the particular sectors[22-24]. Although IIM considers the inoperability of interconnected sectors within an economy, it neglects the influences like demand perturbations and labor constraints. Later, Post-disaster Imbalances Model was developed by Steenge and Bočkarjova (2007)[25], in which a closed form IO model was introduced to consider the linkage between household demand and labor power in a disaster aftermath.

Among IO models, the regional adaptive IO model (ARIO) built by Hallegatte (2008)[1] made significant contributions to the development of IO analysis and natural disaster impact assessment. ARIO is a hybrid modelling method based on Brookshire et al. (1997)[26]. By incorporating the 'production capacity' factor and adaptive behavior after the disaster, ARIO is able to analyze over-production possibilities and import substitutions, as well as assess production bottlenecks and various substitution scenarios[27]. On this basis, Li et al. (2013)[13] constructed a Basic Dynamic Inequalities Model (BDI) to assess an imbalanced economic recovery in a post-disaster period by integrating both capital and labor constraints. Koks et al. (2015)[28] employed both the imbalanced BDI and ARIO model to simulate production loss and economic recovery after a disaster affecting the harbor area of Rotterdam (the Netherlands). A functional relationship between industrial value-added and total output of each sector was introduced in this study. More recently, Mendoza-Tinoco et al. (2017)[11], Zeng et al., (2019)[19] and Mendoza-Tinoco et al. (2020)[29] developed a Flood Footprint Model based on the ARIO model to quantify the economic impact of floods within and across regions by considering factors like labor and capital constraints, supply bottlenecks, adaption of consumer behavior, recovery of economic imbalances, and rationing scheme of available resources. These model aspects were parameterized according to real events, in contrast to previous studies.

Regarding CGE models, Shoven and Whalley (1992)[30] explained this modeling class as a "multi-market simulation model based on the simultaneous optimizing behavior of individual consumers and firms, subject to economic account balance and resource constraints". A CGE model is able to analyze altering market conditions and behavioral response caused by input constraints by incorporating several policy factors and relative price influence[31-33]. In the literature of disaster risk assessments, Rose and Liao (2005)[33] advanced CGE models by improving the behavioral parameters that link production functions and producer adaptations. More recently, Carreral et al. (2015)[34] built an integrated approach by combining a CGE model with high resolution spatial damage data to track the economic consequences of the 2000 Po river flood in Italy. Meanwhile, Haddad and Teixeira (2015)[35] proposed a spatial CGE model to quantify the economic damage of flood in the São Paulo Metropolitan Region in Brazil.

However, both IO (including ARIO) and CGE have certain disadvantages. The main challenge of IO is that the technological ties are rigid, resulting in a lack of responses to price and of substitutions in markets[25]. Alternative suppliers or inputs from external sources leads the IO model to overestimate economic losses. Although ARIO made improvement on the rigid ties of IO, it is still not able to consider factors like relative price changes and industrial production behavior. On the contrary, instantaneous adjustments of relative prices are allowed in CGE models, such that price effects can be reflected. Since flexible substitution possibilities are the basic assumption of CGE, market flexibility is overly optimistic in CGE compared with the adaptive capabilities of the real economy[34,36]. In addition, fewer sectors are generally represented in CGE models than in IO models because CGE models require more extensive data on cross-sectoral interactions, such as elasticities [1,3,9,31,33]. Hence, due to its rigidity and simplicity in terms of parameterization, IO models are more widely used for short-term economic damage estimation of sudden-onset events [11,13,28]; while CGE models are more suitable for assessing long-term processes, as both price and policy influence are taken into account.

As stated in the introduction, a common limitation of both approaches is the assumption of ubiquitous information, which is often implicit. However, post-disaster decision-making is often done with limited information[37,38]. Especially in complex supply chain networks, economic agents often do not have complete access to all the information of other players. The decision-making process under incomplete information is very different from the decision-making process under complete information[37,39,40]. The impact of information on the propagation of economic impact of disasters is worth investigating.

In this study, we focus on this gap in the existing modeling literature and set out to model the decision-making process of economic agents in disaster aftermath. We develop a new dynamic recursive model that goes beyond the current state of literature in the following way: 1) all relevant decisions are governed by local optimization principles, e.g., firms decide on their production level by profit optimization and households distribute their income to commodity consumption and saving based on utility maximization; 2) incomplete information assumptions are made, i.e., economic agents may not know all the current information when they make decisions and they need to form expectations for others' actions in that case.

3. Model description

This section presents the newly developed recursive dynamic model. In section 3.1, we introduce the general structure of the model, including the economic agents, their basic behaviors, and the interaction between them. Then, the dynamics of the model are presented in section 3.2.

3.1 Base settings

We consider an economy consisting of sub-economies distributed in different regions (see Figure 1). Each sub-economy consists of two types of agents, i.e., a set of representative firms producing different commodities and a representative household. We assume that time is discrete and indexed by t.

We assume that each firm produces a unique commodity. To carry out its production process, firms needs intermediates inputs (i.e., commodities) supplied by other firms and primary inputs (e.g., labor and capital) supplied by households. As in Hallegatte (2014)[3], we use an inventory system to model the dynamics of the intermediates hold by firms. Figure 1 gives out a schematic diagram of the production process of a firm. The firm distributes its products to its clients (i.e., other firms and households) according to the orders it received in the previous period, i.e., $t-1$. Meanwhile, the firm orders intermediate inputs from its suppliers.

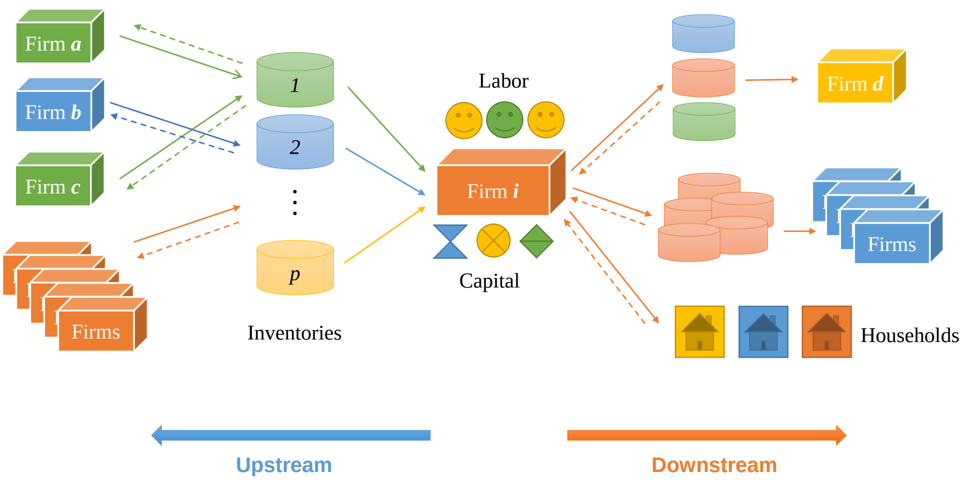

Figure 1 | A schematic diagram of the production process of a firm. Products flow from left to right (solid line), whereas orders flow in the opposite direction (dotted line).

We represent the production function of the firms with a sequence of nested Constant Elasticity of Substitution (CES) functions (in the form in Equation 1[41]; please reach to Equation 9-12 for more detail of the nested structure) that aims to re-produce the substitution possibilities across the full set of inputs. The top-level nest is composed of two aggregate composite bundles—intermediate demand and value added. The second level nests decompose each of the two aggregate nests into their components: demand for individual intermediate goods and demand for individual factors. A final nest decomposes demand for the composite good into domestic and imported components[41].

$$y = \beta \left(\sum_{i=1}^{n} \alpha_i \cdot x_i^{\rho} \right)^{1/\rho} \qquad \text{(Equation 1)}$$

Households obtain income, inc_t, through collecting revenue from labor, wl_t, and capital, wk_t, and trade balance (net export), tb_t, as shown in Equation 2.

$$inc_t = wl_t + wk_t + tb_t \qquad \text{(Equation 2)}$$

Regional income is used for consumption and saving as shown in Equation 3,

$$inc_t = exp_t = expc_t + exps_t \qquad \text{(Equation 3)}$$

where exp_t denotes the total expenditure in period t, $expc_t$ and $exps_t$ denote the money used for consumption and saving in period t, respectively. We assume that expenditure on consumption, $expc_t$, is non-negative, while expenditure on saving, $exps_t$, can take negative values. A positive $exps_t$ means that the regional household increases its savings, while a negative $exps_t$ means the regional household uses some of its saving to buy goods in period t.

A top-level utility function, using a CES specification, governs the allocation of expenditure between consumption and savings. More specifically, households maximize utility:

$$u_t = \beta_u \left(\alpha_u \cdot uc_t^{\rho_u} + (1-\alpha_u) \cdot us_t^{\rho_u} \right)^{1/\rho_u} \qquad \text{(Equation 4)}$$

where u_t denotes the overall utility of the household, uc_t and us_t denote the utility come from the commodity consumption and the saving (consumption in the future), respectively. Parameter α_u and ρ_u denotes the share coefficient and substitution parameter of the utility function. Saving is a unitary good and we have the following relationship between us_t and the saving in period t, sav_t:

$$us_t = sav_t \qquad \text{(Equation 5)}$$

$$sav_t = sav_{t-1} + exps_t \qquad \text{(Equation 6)}$$

For consumption, we also use nested CES form functions to relate overall sub-utility, uc_t, to consumption of individual commodities. Final goods produced by different producers are treated as differentiated goods, and this model assumes that there is limited substitution instead of perfect substitution among different final goods. Hence, a two-level nested structure is used: the first level aggregates the different types of goods, and the second level aggregates each type of goods from different regions.

The setting of such a utility system can reflect the three practically expected characteristics of consumer behavior in disaster aftermath: (i) When commodity prices increase significantly due to the disaster, consumers temporarily reduce consumption and increase savings; (ii) When income is reduced by the disaster, e.g., decrease in wl_t or wk_t, consumers use part of their savings to consume; (iii) When product supply gradually recovers (commodity prices decrease), consumers that have made savings during the disaster (see behavior (i)) use such additional savings to purchase goods. The results will show a characteristic of "retaliatory consumption" in the recovery process.

3.2 Dynamics

During each period t, the following sequence of events unfolds (Figure 2):

- Firms choose the production level that maximizes profits based on their own situation (the amount of inventory, labor, and capital available; and the corresponding cost) and the orders they received in previous period, i.e., $t-1$.
- Firms distribute products to their clients (other firms or households) pay wages and capital rent. Firms update their inventory, while households update their income and saving.
- Firms issue orders to their suppliers of intermediates on the basis of (1) the orders they expect to receive in the next period; (2) the expected supply-curve of other firms in the next period; and (3) inventories. Firms allocate orders to minimize costs.
- Households issue orders to their suppliers of final products. This process is governed by the utility-maximizing problem.

These steps are iterated, which constitutes the dynamics of the model. We descript each event in details in sections 3.2.1 to 3.2.3.

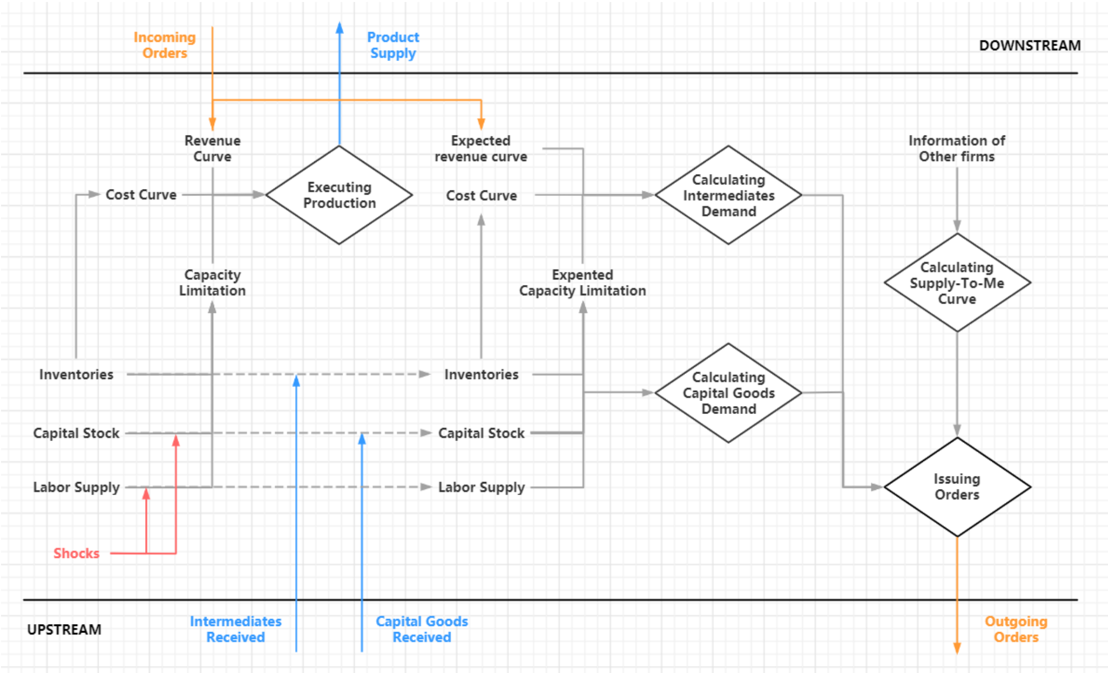

Figure 2 | Sequence of events in one period for a firm. The orange line represents the flow of orders, while the blue line represents the flow of products. The red line represents the shocks. The grey line represents the flow of the information. The dashed arrows indicate the update of self-account (not flow from one to another). The upstream represents the suppliers of the firm, while the downstream represents the clients of the firm.

3.2.1 Commodity supply

Commodity supply in each period is governed by the profit maximization problem of each firm. Before making its production decision, the information hold by firm i includes: (1) the quantity of inventories; (2) the average cost of inventories; (3) the relationship between the amount of labor and the cost of labor (i.e. the wage rate); (4) the relationship between the amount of capital and the cost of capital; (5) the orders it received in previous period, defined by a tuple of the quantity demanded and its reservation price.

Because we focus on the short-term dynamics after the disaster, we assume that labor and capital cannot flow freely between sectors. After a disaster, if a firm wants its workers and capital to work more hours, it needs to pay higher costs. Under these conditions, the commodity supply of the firm is obtained at the intersection of the cost curve and the demand curve. An illustration can be found in Figure 3. The blue curve in Figure 3 represents the demand curve of a firm. In a general case (Figure 3A), the orders received by the firm, form a stepped demand curve, while in the equilibrium case (Figure 3B), all reservation prices of the orders are equal to 1 and the demand curve is a horizontal line. The orange curve is the cost curve of the firm in the short term, which represents how variable costs increase with an increase in outputs. The intersect of the demand curve and the cost curve determines the profit-maximizing production level Q*. When a severe shortage of input occur, it may be impossible for firm to meet the demand (i.e., when the two curves no longer intersect). In this special case, the firm's profit-maximizing commodity supply is the maximum quantity that it can produce (Fig.3C).

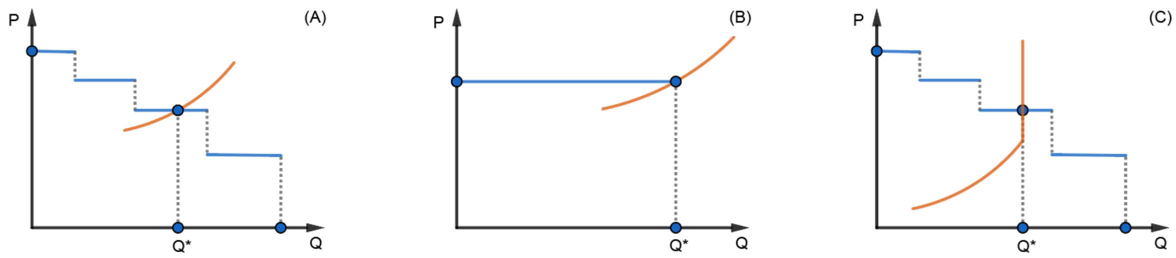

Figure 3 | Illustration of how a firm determines its profit-maximizing production level (Q*) in disequilibrium situations arising in the disaster aftermath (A), in the equilibrium situation (B), and in the situation that the firm reaches the upper limit of overproduction capacity (C). The x-axis represents the quantity, the y-axis represents the price. The orange curve represents the cost curve of the firm and the blue curve represents the demand curve of the firm (all the orders received by the firm form a stepped demand curve in a disequilibrium situation and a horizontal line in an equilibrium situation).

Technically, the complete optimization problem of a firm is as follows. The objective function maximizes the production level, Q_t:

$$\max \ Q_t \qquad \text{(Equation 7)}$$

The constraints can be categorized into four categories. The first category is the profitability constraint. It requires that the corresponding cost, P_t, to the supply level Q_t should not be greater than the corresponding demand price, $P_d(Q_t)$—the demand curve, under that supply level.

$$P_d(Q_t) \geq P_t \qquad \text{(Equation 8)}$$

The second category comprises the nested CES production functions (Equation 9-12) and the corresponding cost relationships (Equation 13-16).

$$Q_t = b\left(a \cdot QV_t^{\rho} + (1-a) \cdot QM_t^{\rho}\right)^{1/\rho} \qquad \text{(Equation 9)}$$

$$QV_t = bv \cdot \left(\sum\nolimits_{\text{fac}} av_{\text{fac}} \cdot QFE_{\text{fac},t}^{\rho v}\right)^{1/\rho v} \qquad \text{(Equation 10)}$$

$$QM_t = bm \cdot \left(\sum\nolimits_{\text{com}} am_{\text{com}} \cdot QFA_{\text{com},t}^{\rho m}\right)^{1/\rho m} \qquad \text{(Equation 11)}$$

$$QFA_{\text{com},t} = bs_{\text{com}} \cdot \left(\sum\nolimits_{\text{reg}} as_{\text{com,reg}} \cdot QFAS_{\text{com,reg},t}^{\rho s_{\text{com}}}\right)^{1/\rho s_{\text{com}}} \qquad \text{(Equation 12)}$$

$$P_t \cdot Q_t = PV_t \cdot QV_t + PM_t \cdot QM_t \quad \text{(Equation 13)}$$

$$PV_t \cdot QV_t = \sum_{\text{fac}} PFE_{\text{fac},t} \cdot QFE_{\text{fac},t} \quad \text{(Equation 14)}$$

$$PM_t \cdot QM_t = \sum_{\text{com}} PFA_{\text{com},t} \cdot QFA_{\text{com},t} \quad \text{(Equation 15)}$$

$$PFA_{\text{com},t} \cdot QFA_{\text{com},t} = \sum_{\text{reg}} PFAS_{\text{com,reg},t} \cdot QFAS_{\text{com,reg},t} \quad \text{(Equation 16)}$$

Where fac, com, reg denotes the production factor index (L and K), commodity index, and region index, respectively; Q_t, QV_t, QM_t, $QFE_{fac,t}$, $QFA_{com,t}$, $QFAS_{com,reg,t}$ denotes the total output of a firm, the value-added bundle, the intermediate demand bundle, the factor demand, the intermediate demand for composite commodity com (sums of one commodities come from different regions), and the intermediate demand for commodity com from region reg, respectively; P_t, PV_t, PM_t, $PFE_{fac,t}$, $PFA_{com,t}$, $PFAS_{com,reg,t}$ denotes the price of the total output of a firm, the value-added bundle, the intermediate demand bundle, the factor demand, the intermediate demand for composite commodity com, and the intermediate demand for commodity com from region reg, respectively. The other arguments in the above equations represent parameters for the various CES functions.

The third category of constraints to the optimization problem of the firm comprises the relationships between factor demand and factor prices (Equation 17 and 18).

$$QFE_{L,t} = QL_{SW,t} \cdot (PFE_{L,t})^{\tau_L} \quad \text{(Equation 17)}$$

$$QFE_{K,t} = QK_{SW,t} \cdot (PFE_{K,t})^{\tau_K} \quad \text{(Equation 18)}$$

where $QL_{SW,t}$ and $QK_{SW,t}$ denotes the amount of labor and productive capital hold by undamaged firms (denoted by subscript SW, which stands for "still working") in period t, respectively.

The fourth category of constraints to the optimization problem of the firm comprises constraints from inventories and factor input (Equation 19-21).

$$QFAS_{\text{com,reg},t} \le QINV_{\text{com,reg},t} \quad \text{(Equation 19)}$$

$$QFE_{L,t} \le \alpha_L \cdot QL_{SW,t} \quad \text{(Equation 20)}$$

$$QFE_{K,t} \le \alpha_K \cdot QK_{SW,t} \quad \text{(Equation 21)}$$

where $QINV_{\text{com,reg},t}$ represents the amount of inventories the firm holds in period t. Parameters α_L and α_K represent the upper limits of idle productivity, also called overproduction capacities[1], that can be enabled of labor and capital, respectively.

By solving the above problem, the firm obtains the optimal production level in period t. These products will be distributed to its clients (i.e., firms and households) according to their orders. Only orders with a reservation price higher than the current production cost of the firm will be filled (Fig.3) and the firm will charge the reservation price. Downstream firms will put the received goods into inventories for use as intermediates in subsequent production periods. Followed by this, the quantity of inventories held by firms and the corresponding average cost will be updated in the following way.

$$QINV_{\text{com,reg},t} = QINV_{\text{com,reg},t-1} - QFAS_{\text{com,reg},t} + QODF_{\text{com,reg},t}$$

$$PINV_{\text{com,reg},t} = (PINV_{\text{com,reg},t-1}(QINV_{\text{com,reg},t-1} - QFAS_{\text{com,reg},t}) + PODF_{\text{com,reg},t} QODF_{\text{com,reg},t}) / QINV_{\text{com,reg},t}$$

where $QODF_{com,reg,t}$ denotes the quantity of the received goods, while $PODF_{com,reg,t}$ denotes the price of the received goods.

3.2.2 Demand requests from firms

Firms allocates orders in two steps. The first step is to estimate the output of the next period and the corresponding inputs required, based on (1) its current situation and (2) the order it expects to receive in the next period. The second step is to determine the price at which it will place the orders—i.e., , the reservation price—based on its predictions of the amount of intermediate products it needs in the next period, calculated in step (1), and its estimates of the supply curve of other firms.

In the first step, firms solve the profit maximization problem again. The differences from optimization problem used to determine the production level, described in Section 3.2.1, are twofold.

(1) The firm's inventory, including quantity and price (average cost), has been updated. Such information conveys the supply and demand relationship of commodities in the market to the firm, enabling it to make corresponding adjustment;

(2) The firm does not know how many orders it will receive and how much capital and labor will be available in the next period. The lack of these two information constraints the firm's optimization behavior.

How much each firm knows about the situation of the other agents determines the accuracy of its estimates. By status, we mean: the quantity and price of their inventories, the availability of capital and labor, and the orders that they will receive in the next period. In the model, we can assume different levels of information sharing and analyze the respective impact on the post-disaster dynamics.

Technically, the optimization problem only differs from the one described in Section 3.2.1, by four equations. We replace Equation 8 with Equation 22:

$$P_d^{exp}(Q_{t+1}) \geq P_{t+1} \quad \text{(Equation 22)}$$

and replace Equation 19, 20, and 21 with Equation 23, 24, and 25:

$$QFAS_{\text{com,reg},t+1} \leq QINV_{\text{com,reg},t+1} \quad \text{(Equation 23)}$$

$$QFE_{L,t+1} \leq \alpha_L \cdot QL_{SW,t+1}^{exp} \quad \text{(Equation 24)}$$

$$QFE_{K,t+1} \leq \alpha_K \cdot QK_{SW,t+1}^{exp} \quad \text{(Equation 25)}$$

where the superscript exp denotes expected values. By solving this optimization problem, we get the quantity of intermediate products that the firm expects to use in the next period, i.e., $QFAS_{\text{com,reg},t+1}^{exp}$.

After determining the quantities of intermediate product the firm intends to order, the next step is to determine the reservation prices. To that end, the firm estimates the status of the other firms from which it wants to order intermediate products. We assume that, based on this information, the firm chooses a reservation price. The reservation price is the lowest price at which its supplier, according the firm's estimates, will accept to fulfill the order.

Technically, a firm calculates the supply of other firms at various reservation prices based on its estimates about their information about other firms and households. We can call this relationship a "supply-to-me" curve. The firm chooses the appropriate reservation price according to this curve.

3.2.3 Demand requests from households

In each period, the regions' representative households determine how much goods they consume by maximizing their utility. Households obtain utility by allocating income to consumption and savings (to some extent, saving means future consumption of goods). The two are substitutes for each other and are summed up by the CES utility function.

We assume that one unit of saving brings one unit of utility (unitary goods). Note that, we do not consider the time preference of consumption here, as the model focuses on the short-term assessment. Modeling savings helps characterize changes in consumer spending dynamics after a disaster (such as retaliatory consumption), which is often not captured in the traditional dynamic IO model.

4. An illustrative example

We analyze the response of the model to production interruptions triggered by a stylized unexpected adverse event. We use this example to illustrate the mechanisms of the model with a simple setting and focus on the qualitative behavior of the simulated post-disaster dynamics.

The hypothetical economic network used for pre-disaster equilibrium is shown in Table 1. It includes the supply-consumer links between 4 firms in two sectors and 2 households, abbreviated hhlds. Households provides labor and capital to firms in their region, and purchases goods from all regions. Firm 1 and 2 and hhld 1 are in one region, and firm 3 and 4 and hhld 2 are in another. Each value in Table 1 represents the goods or services provided by the agent corresponding to the row to the agent corresponding to the column in each day. Household 1 provide capital and labor for firm 1 and 2, while household 2 for firm 3 and 4. We suppose that labor and capital cannot flow freely between firms in the short term.

Table 1 *A hypothetical economic network*

		Consumers					
		firm 1	**firm 2**	**firm 3**	**firm 4**	**hhld 1**	**hhld 2**
Suppliers	**firm 1**	700	600	500	50	750	400
	firm 2	500	300	400	50	500	250
	firm 3	200	50	900	200	1000	1650
	firm 4	100	50	200	200	250	200
	labor	650	400	1100	350		
	capital	850	600	900	150		

We first run the model without any external shocks. We find that the model can reproduce the pre-disaster equilibrium as presented in Table 1. In the following counterfactual, we assume that firm 1 experiences, due to a disaster event, a labor supply shock for one week, in which 5% of its workforce are no longer available.

4.1 Decision-making processes under incomplete information

In this study, one of the most important characteristics of economic agents is that they need to make decisions with incomplete information. Here, we take a closer look at the results from the decision-making processes of in the periods just after the disaster.

In each time step, i.e. one day in the case of our modeling exercise, firms need to anticipate their production levels for the next time step to determine how much inputs they need to order from their suppliers. To do this, firms need to form expectations about the orders they will receive in the next period.

First, we assume that there is no transmission of information between firms. Each firm only makes decisions based on historical information[1]. In this case, the affected firm assumes that the orders it receives in the next period will be the same as the those of the current period[2], which is one type of the commonly called "adaptive expectations"[42]. Therefore, in period 3 (the first period in which the labor supply shock affects firm 1), the total orders that firms expect to receive in period 4 are shown in Table 2.

Table 2 *Period-4 orders estimated in period 3 based on historical information*

	Expected orders from						Total expected orders	
	firm 1	**firm 2**	**firm 3**	**firm 4**	**hhld 1**	**hhld 2**		
firm 1	700	600	500	50	750	400	3000	Quantity
firm 2	500	300	400	50	500	250	4000	
firm 3	200	50	900	200	1000	1650	2000	
firm 4	100	50	200	200	250	200	1000	
firm 1	1	1	1	1	1	1		Price
firm 2	1	1	1	1	1	1		
firm 3	1	1	1	1	1	1		
firm 4	1	1	1	1	1	1		

According to the expected orders and the firm's own situation, firms will form an expectation on their production level in for the next period, which is the level of output that maximizes profit under current expectations. The result, in terms of quantities, is 2933.4 for firm 1, 4000 for firm 2, 2000 for firm 3, and 1000 for firm 4. Although the total expected orders for firm 1 is 3000, its production level is 2933.4. It is because it cannot immediately compensate for the 5% drop of workforce (it cannot hire more labor nor capital).

Based on this result, firms issue orders to their suppliers, shown in Table 3. By comparing Table 3 with the pre-disasters orders, shown on Table 1, we see that the orders issued by firm 1 have decreased significantly due to the labor supply shock, while the order of other firms remains unchanged. This result reflects the difference between decision-making results under incomplete information and under complete information. With complete information, that is, firms 2, 3, and 4 know that firm 1's demand for them will decline, they would choose a lower production level to reduce the cost of intermediate products.

Table 3 *Orders issued in period 3 based on historical information*

	Orders issued to				Total expected orders	
	firm 1	**firm 2**	**firm 3**	**firm 4**		
firm 1	684.5	488.9	195.6	97.8	2933.4	Quantity
firm 2	600.0	300.0	50.0	50.0	4000	
firm 3	500.0	400.0	900.0	200.0	2000	

[1] It may be an exaggeration to make this assumption in a game with only 6 participants. But it may be true in a complex real-world economic network.

[2] We did not assume that the firm itself can obtain its own information. Mainly because in real applications, each firm more likely represents an economic sector, which is a combination of many firms.

firm 4	50.0	50.0	200.0	200.0	1000	
firm 1	1.155	0.997	0.999	0.999		Price
firm 2	1.155	1.000	1.000	1.000		
firm 3	1.155	1.000	1.000	1.000		
firm 4	1.155	1.000	1.000	1.000		

Last, we turn to the production decisions of firms in period 4. Again, according to the received orders and their own conditions, the firms produce ir to maximize profits. The result is 2981.9 for firm 1, 3979.8 for firm 2, 1980.1 for firm 3 and 993.7 for firm 4. The usage of the intermediates is shown in Table 4.

Table 4 *Intermediates usage in period 4*

	Intermediates usage from			
	firm 1	**firm 2**	**firm 3**	**firm 4**
firm 1	695.8	497.0	198.8	99.4
firm 2	594.0	297.0	49.5	49.5
firm 3	497.5	398.0	895.4	199.0
firm 4	49.7	49.7	198.7	198.7

By comparing Table 2 with Table 4, we can derive two key messages. (1) Out of equilibrium, firms form erroneous expectations due to a lack of information on other firms' situation. For example, firm 1's demand for intermediate products to other firms will decline due to its own production capacity decline (Table 2 and 3). However, because firms 2, 3, and 4 are not aware of it, they expect that their output in period 4 would be greater than their actual output in period 4. These erroneous expectations further affected intermediate goods orders. Firms 2, 3, and 4 issued more orders than they actually needed (Table 3 and 4).

(2) Prices will be affected by erroneous expectations. As can be seen from Table 3, the price of firm 1's products suddenly increased by about 15.5%. If firms 2-4 would have known this, their demands would have declined when making decisions, and they would decrease their orders to other firms, which would reduce the cost of intermediate products.

Such erroneous expectations caused by incomplete information will be further transmitted to the next periods. We will show this in section 4.2.

4.2 Dynamics of production and prices

In Section 4.1, we investigated the dynamics of the period just after the disaster. Figures 4 and 5 give out the dynamics of production and prices over a longer time period. Prices shown in Fig. 5 is the average supply price of the firms (firm provides products to its clients at different prices based on their reservation prices).

Two featured periods can be seen from the out-of-equilibrium dynamics shown in Fig. 4 and 5. The first one is a period of fluctuations until day 35. In this stage, the sudden shock caused a drop in the production level of firm 1 which started the fluctuation of the whole system. Along with fluctuations in production levels, prices have also experienced huge fluctuations (Fig. 5). The reason for these fluctuations is that firms cannot form accurate expectations for other agents' decisions in the rapidly changing economic environment, as shown in section 4.1. In this stage, the production of firm 1, the affected firm, suffered a drop of about 3% in the first ten days. The production level gradually increased after the labor restrictions were lifted, exceeding the level in pre-disaster, which caused by the demand to restore the inventories of the other firms.

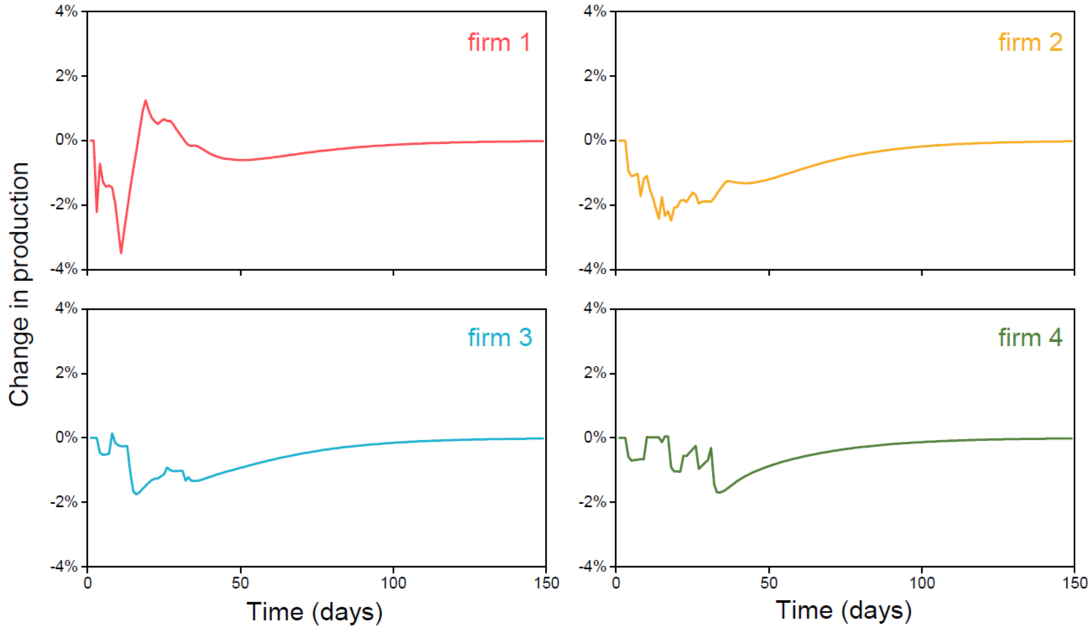

Figure 4 | Dynamics of production.

Following the fluctuating period, there is a smooth relaxation period until the system reaches the pre-disaster equilibrium. In this stage, the economic environment is no longer rapidly fluctuating, such that the expectations are accurate enough to lead the system back to equilibrium in a smooth way.

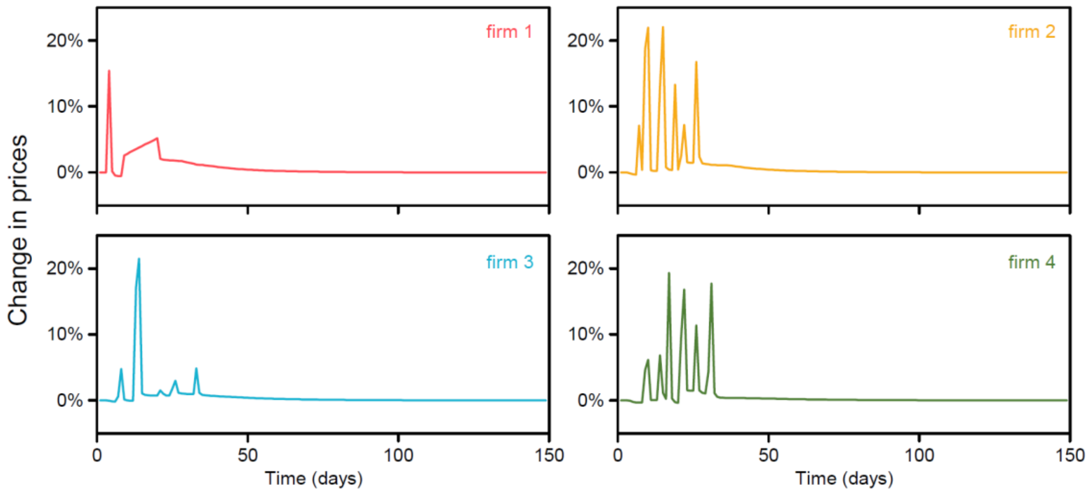

Figure 5 | Dynamics of prices.

4.3 Dynamics of household savings

In addition to the strategic behavior of the firms, another factor that has an important impact on disaster propagation and post-disaster economic dynamics is the strategic behavior of households through savings, which is often ignored in IO-based models. In our model, households will allocate income to consumption and savings based on the price of commodities. Figure 6 shows the saving dynamics. The two top panels show the changes in prices paid by households to the products of the shocked firm, i.e., firm 1. The two bottom panels show the changes in savings (the money they have in their savings bank account) of households.

In the dynamics of savings of hhld 1, we see three stages. From Figure 6, we can see that the savings of hhld 1 dropped by about 1% in the initial shock stage. We call this "savings as supplement". After firm 1 experience the shock, its commodity prices rise (Fig. 6), and the labor compensation collected by hhld 1 from the company decreases. Under these two changes, the utility of hhld 1 dropped significantly due to the decline in commodity consumption. For example, the decline of daily necessities such as food will seriously affect utility. At this stage, hhld 1 will use part of its savings (we assume each household have $500 in their account in the equilibrium) to compensate for the decline in income and the rise in commodity prices.

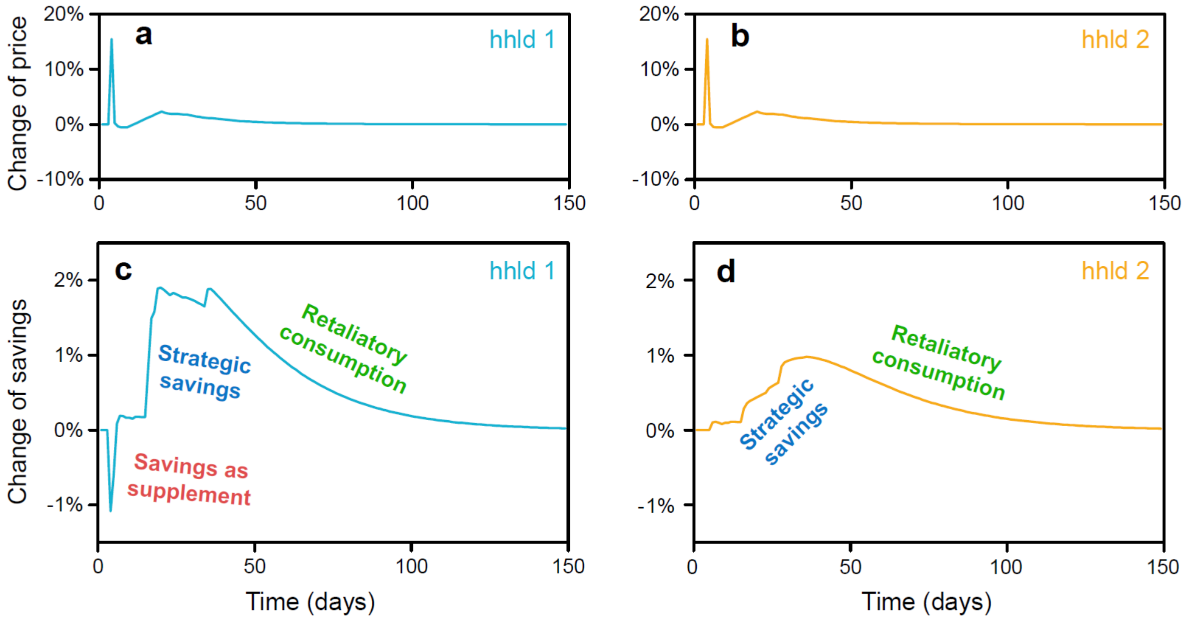

Figure 6 | Dynamics of savings of households.

The second stage is "strategic savings". During this period, hhld 1's savings increase by about 2% (Fig. 6c). After the initial shock, the decline in income and the increase in prices gradually ease (Fig. 6a). At this stage, hhld 1 no longer has a significant lower consumption level like in the first stage. Here, higher commodity prices make it prefer to save the money for the future.

The third stage is what we call in this report "retaliatory consumption". At this stage, hhld 1 uses the previously increased savings for consumption, and the savings level returned to the pre-disaster level (Fig. 6c). In this stage, the economy is less volatile, which helps expectations of firms better match reality, and thus commodity prices have gradually fallen back to pre-disaster levels. During these periods, hhld 1 use the excess savings accumulated in the previous stage for commodity consumption.

We have seen similar stages in dynamics of savings of hhld 2, with two differences (Fig. 6c and 6d). The first point is that hhld 2 does not experience a "savings as supplement" stage. This is because its income did not suffer any direct impact from the disaster. In addition, the increase in its savings is smaller than that of hhld 1 during the entire fluctuation process, although they have experienced similar commodity price changes. This is because hhld 2 is relatively more dependent on the products of firm 3 and 4, while hhld 1 is more dependent on the products of firm 1 and 2.

5. Concluding remarks

This report proposes a new approach for analyzing the propagation of disaster shocks in supply-chain networks. In the proposed model, the behaviors of economic agents (firms and households) are governed by local optimization principles, which avoid the need for multiple ad-hoc behavior rules, and enable the modeling of incomplete information. We argue that such an approach represents a more realistic situation of economic agents in the modern complex supply-chain networks, especially in the disaster aftermath. Since the amount of information each agent holds when making decisions can be set flexibly, the proposed model opens up the possibility to analyze the impacts of information on disaster propagation and assess the value of information in reducing indirect losses from disasters. For example, if we assume that all firms and households know all the conditions of other firms, we can expect shorter fluctuations after the disaster. However, if we assume that firms only estimate the future situation of the other firms based on the past information and not based on the present situation, then we will expect a longer fluctuation duration after the disaster. Through counterfactual settings, we can evaluate the effect of information on reducing disaster losses.

We tested this model by applying it to a hypothetical input-output table. It qualitatively reproduces the expected economic dynamics in a post-disaster phase. The inaccurate expectations due to incomplete information in a rapidly changing economic environment is captured by the model. This mechanism is the source of the large fluctuations in output and prices after the disaster. Some typical post-disaster economic dynamics are also reflected in the results of the model. For example, the dynamics of household savings. The intensity and speed of the dynamics reflected in the results may be different from actual intuition because the data and behavioral parameters are hypothetical. The performance of the model in a complex real-world network will be further tested in subsequent articles.

Compared with the exogenous setting based on historical experience, ad-hoc rules, whether a certain stage appears in the new model is determined by the characteristics of specific shock and the behavioral parameters of agents. We believe that this comprises several advantages. The first and most important one is it allows us to avoid the risk of subjective misspecification in the assessment model. For example, although a process of "retaliatory consumption" can generally be seen in the recovery stage of a disaster, many researchers believe that retaliatory consumption may not happen after a large-scale disaster shock[43]. If we exogenously set a consumption path that contains retaliatory consumption during an assessment, its accuracy will be difficult to guarantee. The second point is that we no longer need to set the range of changes in savings exogenously based on historical experience.

The proposed model can be easily extended to other information dissemination assumptions. Even each agent holds different information. In this way, in real applications, the loss under different information levels can be evaluated to investigate the role of information in mitigating losses.

As a result of the endogenization of most behaviors of economic agents, one major limit of this model is the need for a large number of behavioral parameters and data of the pre-disaster equilibrium. The Global Trade Analysis Project (GTAP) Database can be a relatively complete source of these data at a national level, but it is hard to collect for a sub-national level. Ideally, a set of parameter estimation procedures, e.g., econometric tools, based on raw data should be prepared. Also, the model currently does not include an investment module, and thus cannot analyze the investment dynamics in the post-disaster period.

Finally, this report mainly focused on developing and presenting the model. Two types of follow-up studies are proposed. The first type is comparisons with IO, CGE, and other widely used models for disaster impact analysis, both theoretical and empirical. Such a comparison will better highlight the distinctive features of the proposed model and is valuable from both a scientific and policy perspective, as the propagation of disaster shocks in supply-chain networks not yet fully be understood and disaster impact loss estimates resulting from a range of model outcomes facilitate better decisions and policy making. The second type is validation and verification of the model in its application in the context of real cases.

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