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Natural Disasters, Cascading Losses, and Economic Complexity: A Multi-layer Behavioral Network Approach

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Natural Disasters, Cascading Losses, and Economic Complexity: A Multi-layer Behavioral Network Approach

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Abstract

Assessing the short-term socio-economic impacts of climate-led disasters on food trade networks requires new bottom-up models and vulnerability metrics rooted in complexity theory. Indeed, such shocks could generate cascading socio-economic losses across the networks layers where emerging agents’ responses could trigger tipping points. We contribute to address this research gap by developing a multi-layer behavioral network methodology composed of multiple spatially-explicit layers populated by heterogeneous interacting agents. Then, by introducing a new multi-layer risk measure called vulnerability rank, or \textit{VRank}, we quantify the stress in the aftermath of a shock. Our approach allows us to analyze both the supply- and the demand-side dimensions of the shock by quantifying short-term behavioral responses, the transmission channels across the layers, the conditions for reaching tipping points, and the feedback on macroeconomic indicators.

By simulating a stylized two-layer supply-side production and demand-side household network model we find that, (i) socio-economic vulnerability to climate-led disasters is cyclical, (ii) the distribution of shocks depends critically on the network structure, and on the speed of supply-side and demand-side responses. Our results suggest that such a multi-layer framework could provide a comprehensive picture of how climate-led shocks cascade and how indirect losses can be measured. This is crucial to inform effective post-disaster policies aimed to build food trade network resilience to climate-led shocks, in particular in more agriculture-dependent bread-basket regions.

\textit{Keywords:} complexity economics, multi-layer networks, behavioral economics, food trade, climate-led shocks, vulnerability rank, post-disaster policy

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1. Introduction

Recent advances in network models have helped to improve to a great extent our understanding of complex patterns of economic activities in a globalized and interconnected world. This is due to their ability to account for spatial and temporal heterogeneity, for bottom-up interactions, and for non-linear feedback loops. These characteristics are crucial to provide a comprehensive assessment of shocks’ distributions, impacts and transition processes, thus going beyond state-of-the-art modeling tools.

In particular, network models have been developed in the domains of complex economic and product spaces (Hidalgo & Hausmann, 2009), technological innovation and diffusion (Balland & Rigby, 2017), migration flows (Hausmann & Neffke, 2019), urban sprawl (Glaeser et al., 1992; Bettencourt et al., 2007), and financial networks (Battiston et al., 2012) (see Section 2 below for a detailed review). Nevertheless, their application to the analysis of the conditions under which a system could adapt to climate-led shocks, and for cascading indirect effects to emerge, could help policy-makers and the disaster-risk reduction (DRR) community to understand the overall shocks’ impacts and to design mitigation measures (Helbing, 2013; Levermann, 2013; Hallegatte & Mach, 2016; IDMC, 2018).

By contributing to this stream of literature, we propose a novel approach to modeling economic systems based on unique, yet co-dependent network layers endowed with bottom-up rules. We develop a spatially-explicit network-based behavioral model where the production supply-side interacts with the household demand-side. With this framework we can assess under which conditions a shock to one part of the network could spread through the interactions within and across the network layers. In addition, we can integrate dimensions that are usually analysed separately, i.e. production and trade (Balland & Rigby, 2017) and human mobility (González et al., 2008).

At the core of our multi-layer behavioral network are bottom-up agent-based rules that define the interactions across and within networks nodes and the environment. Such structures typically represent evolving information flows across different sets of agents that influence their socio-economic response through learning. This allows meso- and macro outcomes to emerge and to potentially feedback on micro-level decisions (Farmer & Foley, 2009). Understanding these micro and meso transmission channels is crucial to inform timely and effective post-disaster policies aimed to build socio-economic resilience to climate-led shocks. This goes beyond the state-of-the-art, where standard economic models usually focus on long-period supply-side analysis (Toya & Skidmore, 2007; Okuyama, 2011), mostly neglecting the distributional effects and the analysis of transmission channels. In particular, with the multi-layer behavioral network methodology we can analyze these short-term distributional impacts of climate-led natural disasters on heterogeneous sectors and communities that are interconnected in a network of food production and food-trade relations (Seekell et al., 2017). Such an analysis can help with adaptation policy especially when time and resources are limited and response time is critical (Naqvi, 2017).

In this paper, we also introduce a new multidimensional risk measure, the Vulnerability Rank, or VRank, which quantifies the magnitude of stress in the multi-layer network in a post climate-led disaster scenario. Our measure is based on recent advances in multidimensional network measures (Gemmetto et al., 2016; Kivelä et al., 2014), which were successfully applied in particular in search algorithms (Brin & Page, 1998; Halu et al., 2013) and financial networks theory (Battiston et al., 2012; Bardoscia et al., 2015).

We present a baseline model, where food production and household layers interact, representing typical agricultural-based, low-income region prone to climate shocks. We test the model by
introducing exogenous climate-led shocks on food production in one part of a spatially-explicit multi-layer network. First, we assess the conditions for climate-led natural disasters shocks to generate cascade indirect losses via the multi-layer network of agents. Second, we identify the patterns of households response to shocks that are able to trigger a main change in socio-economic conditions of the communities involved in the food trade network. Importantly, these include distributive effects (output, price volatility, income inequality) via cross-sector feedbacks. Third, we estimate the $\text{VRank}$, that identifies the highly vulnerable regions.

The remaining paper is organized as follows. Section 2 provides a review of recent applications of network models and of the modelling issues at stake for assessing indirect socio-economic impacts of climate-led disasters. Section 3 presents the characteristics of the multi-layer behavioral network model and Section 4 presents the model. Section 5 discusses the results of the simulation on a food trade network highlighting the supply-side and demand-side drivers of shock cascades and indirect losses. Section 6 concludes by contextualizing the policy relevance of the results and by introducing future avenues of research.

2. Review of the state-of-the-art

In the last decade, network models have gained significant attention for the analysis of complex socio-economic interactions in coupled human-environmental systems. This is due to their ability to address inter-disciplinary aspects that requires dealing with economic complexity, thus going beyond the scope of standard optimization-based modeling tools. Network models have been applied to a diverse array of topics like complex economic and product spaces (Hidalgo et al., 2007; Hidalgo & Hausmann, 2009), technological innovation and diffusion (Balland & Rigby, 2017; Fleming & Sorensen, 2001), coordination games (Goyal & Vega-Redondo, 2005; Galeotti et al., 2009), migration flows (González et al., 2008; Schweitzer et al., 2009; Fagiolo & Mastrorillo, 2014; Hausmann & Nedelkoska, 2018; Hausmann & Neffke, 2019), urban sprawl (Glaeser et al., 1992; Bettencourt et al., 2007; Balland et al., 2018), urban mobility (Hörl, 2017; Horni et al., 2016), and financial networks (Battiston et al., 2012; Acemoglu et al., 2015). This surge has also been supported by better data availability and higher computational power.

With regard to complex networks, multi-layer or multi-dimensional network structures (Schweitzer et al., 2009; Kivelä et al., 2014) received attention, in particular after the financial crisis (Acemoglu et al., 2015; Pilosof et al., 2017). In multi-layer networks, complexity not only plays a role within, but also across different network layers. Such multi-layer systems are at the heart of “systemic risk” analysis, where under specific conditions a shock to a relatively benign part of a network could cause a contagion, potentially leading to systemic effects (Thurner & Poledna, 2013; Battiston et al., 2016). Multi-layer network models are now frequently applied in the domain of finance to the analysis of cascading impacts. Nevertheless, their development and application to the analysis of the linkages between supply-side networks (such as production and trade) and demand-side networks (such as consumption and migration) is still at an infant stage (Fagiolo & Mastrorillo, 2014; Naqvi, 2017).

In the aftermath of the last financial crisis, network models contributed to assess the conditions for the onset of systemic risk in the financial sector by contributing to analyze shocks reverberation across the network of financial contracts, and to assess both first and second-round losses (Battiston et al., 2012, 2014).

This recent stream of network models applications plays a relevant role in the current debate among policy makers, central banks and financial regulators on how to build economic and financial
systems resilience to climate risks (Lamperti et al., 2018). Indeed, there is growing awareness of the fact that traditional climate economics and financial risk models are not properly equipped to consider the characteristics of climate-related shocks as well as of opportunities from building resilience to shocks, being constrained by equilibrium conditions and linearity of impacts, as well as by representative agents and inter-temporal optimization (Heal & Millner, 2014; Pindyck, 2013; Stern, 2016).

Additionally, it has been increasingly recognized that the assessment of the socio-economic and financial impacts of climate change requires embracing with complexity. This emerges from several issues including the nature of climate impacts characterized by fat tails distributions (Ackerman, 2017; Weitzman, 2009), the non-linearity between climate impacts and heterogeneous socio-economic agents’ reactions (Farmer et al., 2015; Mercure et al., 2016), the feedback loops across agents and sectors, the time and path dependence of policy responses (Farmer & Foley, 2009).

Post climate-led natural disasters’ cascading events can result in both direct and indirect losses. While the direct costs of such climate-led shocks have been the subject of research work especially on macro outcomes (Hallegatte & Mach, 2016; Rose, 2007), the channels of shock transmission through which indirect losses generate, the channels of risk amplification, and the conditions for systemic risk have still to be understood (Lazzaroni & van Bergeijk, 2014). Direct and indirect shocks to socio-economic systems, and their resulting spillovers represent new sources of stress for traditional social safety nets and create vulnerabilities (Hallegatte et al., 2007; Naoussi & Tripier, 2013; Rose, 2004; Ward & Shively, 2012), for example, via population displacement (WB, 2018; IDMC, 2018), or the disruption of critical supply chains (Guha-Sapir & Santos, 2013).

There is consensus among scientists that climate change will result in higher incidences of both sudden and slow-onset climate shocks (IPCC, 2012, 2018) that will invariably affect global production systems especially agriculture (FAO, 2013). This coupled with growing population and higher rates of urbanization, only implies that that global system is slowly being pushed towards its tipping point making it extremely vulnerable to exogenous shocks. This is particularly true of the agriculture sector and food trade networks where a few bread-basket regions supply the world with majority of its essential consumption items (FAO, 2015b; Janetos et al., 2017; Seekell et al., 2017; FAO, 2018). Given that these bread-basket regions employ a large share of the working population, usually at very low wages, a climate-led shock could easily create conditions for food insecurity not only in the region where the shock hits, but in other regions as well through trade and migration (Robalino et al., 2015; Janetos et al., 2017; Gaupp et al., 2017). Thus the distributional impacts of climate shocks are crucial for assessing socio-economic vulnerability (Hallegatte & Przyluski, 2010; Rao et al., 2017; IDMC, 2018) and its non-economic ramifications like geo-political instability and civil unrest to name a few (Puma et al., 2015; GFSP, 2015; Campbell et al., 2016).

Climate-led shocks can impact both the supply-side (through disruption of supply networks) and the demand side (through income losses) (Hallegatte et al., 2007). This can trigger cascading indirect losses that emerge from complex, non-linear spatial-temporal interactions, for example decisions to sell in certain markets or migrate from affected regions to non-affected regions. These results can be driven by threshold dynamics (for example, losses leading people to stay or to migrate to neighboring regions) that are influenced by heterogeneous agents responses to the shocks (Naqvi, 2017). If the behavior leading to the threshold is embraced by a large share of agents, then the meso- and macro outcomes can be considered as co-evolutionary processes that take place through the interaction of multiple, co-dependent, socio-economic network layers. Understanding of these transition pathways in response to specific natural disasters can contribute to broad set of research
agendas in the climate community, for example, impacts of climate shocks on poverty (Hallegatte et al., 2015), migration and displacement (IDMC, 2018), water-food-energy nexus (Tavoni & Levin, 2014; Howarth & Monasterolo, 2016), loss and damage (Mechler & Schinko, 2016), and multiple bread-basket failures (Gaupp et al., 2017; Janetos et al., 2017).

Nevertheless, traditional economic modeling techniques usually prescribe supply-side policies that mostly focus on long-run aggregate outcome variables like output and capital stocks, without considering heterogeneous, and time-delayed agents response in terms of demand-side adjustments. Further, they consider inequality and distributive effects as a short-time effect of the disasters, and thus are not able to identify potential long-term structural changes led by distributive effects (Monasterolo & Raberto, 2019). This is where a new generation of multi-layer behavioral network models have an added value on existing approaches because they allow to integrate the micro-meso and macro level of analysis, accounting for heterogeneous spatial and temporal preferences, asymmetric information, and path-dependence of policy responses within a modular, stock-flow consistent framework. Thus providing a very rich yet under-utilized tool to analyze such systems.

3. The multi-layer behavioral network methodology

3.1. A conceptual multi-layer network approach

One way of modeling economies is to conceptualize them as spatially-explicit multi-layer networks. Networks comprise of nodes, which could include well-defined locations. Depending on the scale of analysis, nodes can represent villages, cities, counties, districts, provinces, or even countries. Nodes are interconnected through links that could represent either physical (roads) or intangible (social/community networks) infrastructures. Nodes can also be connected across various layers, giving rise to a multi-layer structure. Each layer is defined by behavioral rules which determines how nodes interact with each other, while the multi-layer structure determines how nodes interact across layers. This interdependence implies that a seemingly unimportant node in one layer might have a high importance in other layers. In particular, under certain conditions, a shock to this node can trigger a cascading event resulting in a system-wide failure. This phenomenon is known as “systemic risk” and widely applied in the analysis of financial networks (Acemoglu et al., 2015; Battiston et al., 2012).

In Figure 1, we represent a stylized one-country economy as a multidimensional network composed of two network layers, (i) a production layer, which determines how much is produced and traded across the network, and (ii) a household layer, which determines how much labor is available to allow the desired production and how much income is available to consume the production. In the household layer, the movement of workers is based on income signals. The trade of goods across the nodes are determined by price signals. The size and magnitude of the flows across the individual nodes and layers can be attributed to the structural properties of the network, and in particular to the network size, the network link density, and the response times across and within layers.

3.2. A behavioural multi-layer network

Operationalizing a traditional trade network model requires that the nodes in the multi-layer network are endowed with decision making rules that determine the behavioral interaction across and within the socio-economic network layers. At this regard, in the last two decades, agent-based models emerged as a main approach to the analysis of agents economic behaviours when
Figure 1: A stylised multidimensional network framework.

Note: The figure shows the Production and Household layers which are integrated in a socio-economic network. The same network nodes belong to both layers, while the behavioral interactions across and within determine the flows. This is represented as migration or displacement in the household layer, and as trade in the production layer. In this framework, a shock to one node will result in cascading changes across the network.
we depart from the assumptions of agents representativity and rational expectations (Tesfatsion, 2006). Agent-based models are a bottom-up methodology where the interaction of micro-level agents generate “meso” outcomes, which in turn, feedback on the micro-decision making processes (Axelrod & Tesfatsion, 2006; Epstein & Axtell, 1996). These micro-meso interactions are able to capture emerging spatial structures and non-linear interactions that are key to modeling agents reactions to shocks. In particular, they could provide a more realistic and comprehensive analysis of the drivers of transition pathways in response to climate-led disasters at the regional or country level.

Figure 2: Behavioural setup of a two-locations stylized economy.

Note: Figure 2 shows the simplest behavioral interactions that could occur across the two layers shown in 1. Each node follows a circular economy framework where endowments of labor and capital determine income and production levels. Differences in prices across the two locations result in migration and trade flows in a gravity model-like setting.

Figure 2 displays stylized interactions across the two layers described in Figure 1. Each location (or node) is endowed with a (pre-climate shock) stock of capital and labor that characterize the production and household layers respectively. At each location, labor is employed to produce an output in exchange for wages, which they use to consume goods. Through these interactions, each location evolves its own set of wages and goods prices. If the two locations shown in Figure 2 are allowed to interact, the differences in price signals will result in trade and migration flows. For example, households may move to locations offering higher wages and firms may sell to locations where households are able or willing to pay higher prices for the same goods.

In absence of any external input, this two-layer two-location network will achieve a stable distribution of population and goods through the equalization of prices, mimicking gravity models of trade and migration (Anderson, 1979; Strömberg, 2007; Lewer & Van den Berg, 2008). This
price-based economic incentives could be improved and made more realistic (and complex) by embedding additional sociological and institutional behavioural rules. This step would allow to consider non-economic aspects such as socially-defined preferences for finding work and migration destination, community-based decisions, and institutionally driven linkages across nodes, such as trade agreements, resulting weighted, directional, network structures.

3.3. A food trade multi-layer behavioral network

Let us assume that the economy produces two types of goods, that is basic food commodities (for example, rice or wheat) and non-food commodity, in both locations shown in Figure 2. Then, let us consider a climate-led extreme event (for example, a flood or an earthquake) that affects Location 1 by devastating agricultural land and thus leading to a reduction of food output. This shock will immediately result in two key changes in Location 1: (i) a sudden rise in food prices due to lower output, and (ii) an immediate fall in wages due to lower production. As a result, behavioral responses to the shock will be triggered across the two layers in Location 1. Households in Location 1 will respond to the shock by moving to the non-affected Location 2 which offers relatively higher incomes and thus higher purchasing power. However, this additional inflow of population in Location 2 will reduce wages there to the extent to cause overall wages to decline in the whole system.

The demographic shift will also affect the demand for goods. As population moves from Location 1 to 2, the demand for goods also shifts more towards Location 2. The remaining production stock in Location 1 will start selling more in Location 2 due to higher prices, thus contributing to increase the prices in Location 1 and thus further reducing the purchasing power of households in Location 1. This, in turn, will foster more migration from Location 1 to Location 2. Thus, the co-evolutionary movement of labor and goods in a given network structure will determine how prices across the two layers will evolve. Indeed, the movement of goods and labor force will continue till the prices stabilize across the layers. However, interestingly, the transition pathway from the pre-shock distribution to the final post-shock distribution can introduce new sources of vulnerability in the system that might be able to trigger unintended systems response to the initial shock.

3.4. Systems thresholds in a multi-layer behavioral network

Responses of agents to shocks can hit certain thresholds resulting in behavioral regime switches thus changing how interacts take place. In a highly volatile or chaotic state typically observed after climate-led shocks, system such as the food commodity prices considered, this can trigger sudden changes in behavioral regimes across a large set of agents, resulting in highly non-linear transition processes. The ability to model such time-sensitive and endogenous parameters are beyond the scope of state-of-the-art modeling tools implying that decisions do not take place in an environment characterized by full information and optimization routines, rather, they are determined by responses to current and expected economic stimulus. It also implies that an emerging behavior can be governed by the decisions of neighbors through herding and mimicking behavior creating new equilibrium outcomes that representative independent agents might not predict.

Let us consider again our food trade network composed of two layers and two locations. If food has an inelastic demand (as is the case for basic food consumption items), then a price increase implies that households will spend a higher share of their income on that food commodity to stay above some minimum consumption threshold. Falling below this threshold would trigger various income-consumption smoothing strategies. For example, in low-income regions, households can
Figure 3: Thresholds in a multi-layer behavioral network

Note: The figure shows how the thresholds can look like for the household and production layers. Households make consumption decisions based on their income level, price levels, and preferences for a basket of goods. Thus, if income goes up, consumption will also increase. The extent to which goods are consumed depends on their relative price and on the elasticity of demand.
respond by running down savings, selling assets, or borrowing from others (Auffret, 2003; Dercon, 2002; Skoufias, 2003). If all else fails, they might migrate to another location, or remain and be potentially at risk of becoming food insecure. This, in turn, could give rise to new socio-economic vulnerabilities and potentially resulting in abrupt geopolitical policy changes (for example reduce or block trade routes) or political movements which add additional layers of complexity (see for instance the case of the Arab Spring and Brexit).

Like the household layer, the production layer also faces threshold dynamics. Producers sell goods only in the locations where they can make profits or, at least, where they can cover the unit costs of production. This, for example, suggests that affected markets, which have higher production costs and low demand (for example, as a result of out-migration) are likely to be less attractive. Thus, by changing the supply, profit-seeking producers can affect market prices, which feed back on households’ consumption and migration decisions. The combination of these two simple thresholds can however significantly increase the non-linearity in the post-shock transition phase.

4. Basic model description

The core model structure assumes full adjustment of demand and supply through prices across the goods and labor markets layers. This can modified to incorporate frictions, institutional barriers, and path-dependencies which will only make the results stronger. Thus distributional effects shown here are in a best-case full-adjustment scenario.

Each multi-layer network structure contains \( i = \{1, \ldots, n\} \) nodes. Each node \( i \) is endowed with land and capital stock that results in the production of food (\( F \)) and other consumable goods (\( G \)) respectively such that the production set is represented by \( k = \{F, G\} \). The total output produced at a node \( i \) equals \( y_i = \sum_k \beta_k x_{ik} \), where \( \beta_k \) is the weight of product \( k \) at node \( i \). 50% of randomly selected nodes mostly produce food (\( \beta_F = 0.9, \beta_G = 0.1 \)), while the rest mostly produce other consumable goods (\( \beta_G = 0.9, \beta_F = 0.1 \)). For simplicity, all nodes are endowed with the same level of production capacity and productivity levels, such that \( y_i \) equals across all nodes. These assumptions can also be relaxed to have a more complex product space of the type analyzed in Hidalgo & Hausmann (2009). Thus the only variation in the model are randomly generated network structures.

The production at node \( i \) employs all the available labor \( L_i \). Assuming that \( \rho \) is the unit cost of production and labor is the only cost (capital is assumed fixed in the short-run), the income per worker equals \( w_i = (\rho y_i)/L_i \). The income earned by workers is fully spent on the two goods such that a fraction \( \alpha \) is spent on food \( F \), and \( 1 - \alpha \) on good \( G \).\(^1\) From this, the price of the two goods at node \( i \) can be derived as \( p_{iF} = (\alpha w_i L_i)/x_{iF} \) and \( p_{iG} = ((1 - \alpha) w_i L_i)/x_{iG} \) respectively. In nominal terms, the value of the total output produced at a node \( i \) can be derived as \( Y_i = \sum_j x_{ik} p_{ik} \).

If the nodes are allowed to interact, then a gravity model-like specification determines how much is exchanged across the nodes (Fafchamps & Shilpi, 2013; Fagiolo & Mastrorillo, 2014; Hausmann & Nedelkoska, 2018). This is estimated in the model as a logistic function \( \Pi_{ij} \) between node \( i \) and its \( j \) neighbors following a joint-probability distribution of the type: \( \Pi_{ij} = \Pi_{ij}^0 \times (1 - \Pi_{ij}^d) \). In short, the probability of moving to a neighbor \( j \) or \( \Pi_{ij} \) is positively affected by relative economic gains \( \Pi_{ij}^0 \) at location \( j \) and negatively by distance \( \Pi_{ij}^d \) to node \( j \).

\(^1\)Naqvi & Rehm (2014) explore endogenous build-up of saving and inventories in a similar setting.
For migration, the economic gains are determined by real income differences and for trade by relative profit gains. The generic logistic function is of the type \( \Pi_z = \frac{1}{a + be^{-z}} \) where \( \{a, b\} \) are calibration parameters. Additional distributions can also be added to represent non-economic weights, for example, community at destination and other social linkages.\(^2\)

The thresholds discussed in Section 3.4 are introduced in the model as well. First, households adjust their propensity to consume food relative to a minimum consumption value \( \bar{c} \). If their income goes down or food prices go up, then \( \alpha \) will adjust endogenously to ensure that they stay at least at the \( \bar{c} \) level. Since households cannot spend more than what they earn, and they consumption at least \( \bar{\alpha} \), \( \alpha \) is bounded such that \( \bar{\alpha} \leq \alpha \leq 1 \). Like households, producers only sell in markets which give them positive profits. Unlike households, where the decision to migrate is a binary outcome, producers can diversify their portfolio to sell in several markets, adjusting their supply to changes in demand around them. Since producers have a production costs associated with outputs, the difference between the cost and the market prices determines the profit margins. Since the unit cost of production equals \( \rho \) and the market price equals \( p_{ik} \), then the condition \( p_{ik} \geq \rho \), defines the sorting for selling in markets where the markets with the highest profit margin are given priority. If some markets fall below this threshold, or \( p_{ik} < \rho \), then they are excluded from the list. These two thresholds evolve dynamically since all variables are time indexed.

4.1. The VRank multidimensional risk measure

We introduce a new multidimensional risk measure that we call “Vulnerability Rank”, or VRank, to quantify the stress in the system following a climate-led disaster scenario. Our VRank measure is based on recent most relevant advances in multidimensional network measures (Gemmetto et al., 2016; Kivelä et al., 2014). In particular, it stems from the DebtRank financial network risk measure developed by Battiston et al. (2012); Bardoscia et al. (2015) and the Google’s PageRank algorithm (Brin & Page, 1998; Halu et al., 2013).

Vulnerability, particularly in low-income regions, is defined in terms of purchasing power of a minimum consumption bundle. Populations falling below this minimum consumption threshold (\( \bar{c} \) in Figure 3) are labeled “food insecure”, and if their needs are not immediately tended to, then it can result in negative secondary round effects, for example, poor consumption levels and poorer health which can in-turn lower productivity and reduce economic output. Food bundles are well-defined for all countries usually measured in adult-equivalent caloric in-take per capita on which food-based poverty line is measured (FAO, 2013, 2015a).

VRank is formally defined as:

\[
V_{Rank_{it}} = \left( \frac{p_{it} \bar{c}}{w_{it} L_{it}} \sum_{j \neq i} \beta \frac{p_{jt} \bar{c}}{w_{jt} L_{jt}} \right)^{1/2}
\]  \hspace{1cm} (1)

Where \( p_{it} \bar{c} \) is the price of minimum consumption bundle at node \( i \) at time \( t \), \( w_{it} L_{it} \) is total income calculated as wage rate at node \( i \) times the total labor supply. Similarly \( p_{jt} \bar{c} \) and \( w_{jt} L_{jt} \) are the average minimum consumption bundle to income ratio of the \( j \) neighboring nodes of node \( i \), and \( \beta \) is the dampening factor typically set at \( \beta = 0.85 \) (Brin & Page, 1998). In other words, the vulnerability of a node \( i \) is not only defined as the purchasing power of the minimum consumption bundle of a population at a particular node, but also by all its neighboring nodes as well. A lower value of \( V_{Rank_{it}} \) implies lower vulnerability.

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\(^2\)See Naqvi (2017); Naqvi & Rehm (2014) for detailed model calibrations.
The *VRank* formula, captures two key elements. First, it shows the dependence of one node from another in terms of food supply. For instance, a node which does not produce any food commodity would be considered vulnerable in isolation, but if it is connected with several food producing regions that could supply it with food, it would show a much lower vulnerability level. Additionally this node would be in a much better position than a completely isolated food-producing node. Second, it captures the displacement-based linkages. Indeed, a node that produces enough food for its current population might experience a sudden populations inflow from the neighboring areas affected by the shock, thus becoming indirectly vulnerable to the shock in the short-run. Therefore, it emerges that understanding the conditions for the linkages to be a source of resilience or a source of vulnerability for individual nodes is crucial to assess the direct and cascading impacts of the shock within the network.

5. Simulating climate-led shocks in a multi-layer behavioral food network model

A stylized model of food trade is developed based on the multi-layer behavioral network framework described above. In order to simulate the model, we generate random networks with 80 nodes, of which 50% produces food while the rest produce general non-food goods. All nodes have the same initial population of households and quantities of food and non-food goods. Then, three sets of links are generated that connect the nodes representing population flows, food, and non-food flows. Figure 4 shows two sample random networks with these characteristics.

![Figure 4: Random networks](image)

*Note:* Networks are generated in NetLogo, *(Wilensky, 1999).* The networks are composed of food producing (green) and non-food producing (purple) nodes, with link weights representing the level of food flows, and shaded area representing the area affected by the climate-led shock.

Each network runs till it reaches a stable distribution of population, goods, and prices. The food-producing nodes in one part of the network, shown as the grey region in Figure 4, are shocked

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These assumptions can be relaxed as well, but it will be hard to disentangle the changes in outcomes resulting from the shock and distributional endowments.
as a consequence of the climate-led disaster with a resulting reduction in food output. The shock impact ranges from 40% to 80% of output reduction in steps of 10% each. Each shock level is tested on 10 randomly generated networks (or 50 simulations runs in total) to generate distributions. The model runs until prices stabilize. We obtain a 6 to 12 months post-shock adjustment period that indeed mimics the food output shock that is typically faced by low-income food producing countries.

Then, we analyze the distributions of shocks on the systems key macroeconomic indicators in terms of percentage changes from the no-shock baseline scenario (Figure 5). Figure 5a shows the overall output of the economy that shows in average limited variations in comparison to a no-shock baseline scenario. However, it is important to notice that the deviation increases as the shock intensity goes up, in a non-linear way. Figure 5b shows an increase in the relative food-to-labor price ratio. This implies that real income falls, reducing purchasing power that results in an overall decline in consumption levels (Figure 5c). Overall, higher magnitude shocks could create higher volatility in the system and thus stronger distributive effects, according to how the shock is managed and to the initial households vulnerability conditions in the affected Location.

Figure 5: Macroeconomic and distributive effects of the climate-led shock in a 2-layers food network

![Figure 5](image)

Note: In each figure, the x-axis represents different shock levels, while the y-axis shows changes relative to the no-shock baseline scenario. Box plots show medians (box), interquartile ranges (lines), and outliers (dots), for multiple simulation runs within the same shock level.

Figure 6 shows simulation runs with randomly generated networks for an 80% reduction in food output. We notice the emergence of different cycles in the adjustment phase, leading to two main considerations. First, the structure of the network determines the evolving pattern of the cycles, for example, the numbers of nodes affected, the pace of connectivity across layers and their relative response times. Therefore, the same shock can lead to very different patterns even in presence of similar baseline socio-economic structures. Second, if we focus only on the starting point (top-left of Figure 6) and on the end stationary point, we would miss the adjustment pathways of the climate-led shocks. Indeed, larger cycles imply that households experience higher degrees of vulnerability through the post-shock transition phases. This is an important result for post-shock policy responses aimed to minimize the secondary level effects of climate shocks, in particular in low-income countries where most households incomes are mostly allocated to food purchases. For example, the duration of food insecurity crises generated by climate-led disasters, and the scale of internal households migration, might give rise to new socio-economic challenges for governments, such as people falling below the poverty line or becoming food insecure, higher private debt levels,
likelihood of the spread of diseases and civil conflicts (Ghimire et al., 2015; GFSP, 2015).

Figure 6: Cyclical Vulnerability for a 80% food shock

Note: The figure shows the correlation between the percentage changes in relative food-to-labor prices (x-axis) and food consumption levels (y-axis) from the baseline no-shock scenario for the 80% food output loss scenario only. The points of the scatter plot are connected for all time steps and exhibit a cyclical pattern before stabilizing. The x-axis shows the percentage change in the food-to-labor price (relative to the baseline no shock scenario) that increases in average. The y-axis represents the percentage change in food consumption (relative to the baseline) that declines in average.

Finally, Figure 7 provides a breakdown of the 80% food output shock represented via spatial contour plots by plotting the two indicators, that is, the relative food-to-labor price ratio (Fig. 7a), and the average consumption of households (Fig. 7b). The x-axis represents the normalized distance of the nodes from the shocked region, or the fault line. The y-axis represents the density of the nodes, where a low number implies fewer connections to other nodes.

The spatial evolution of average food-to-labor prices and average food consumption indicators is tracked at regular intervals from the time the shock hits the system. In both figures, the high-density nodes closest to the fault line respond faster to the shock than the low-density ones. Higher density also implies that the shock is immediately passed to the neighboring nodes where the response time of low-density nodes is much slower. This slow adjustment in low density nodes can be identified as the wave that moves along the x-axis in both the heat plots in Figure 7. The last time steps highlight the reverberations across the two indicators that bounce back after hitting the boundary of the system.

These results highlight the importance of the spatial layout of the region in assessing the impact of the shock. The shock spreads from the top left corner (high density, nearest to the fault line), ending up at the bottom-right (low density, farthest from the fault line). The stable post-shock distribution shown in the last time step 6-12 months (Figure 7a and 7b) implies that after all the adjustments have stabilized, lower density nodes end up with poorer access to food markets and thus generally show lower food consumption levels.

Finally, Figure 8 shows the results of the 80% food output shock on the node’s vulnerability
Figure 7: Spatial trends

(a) Food-to-labor price ratio
(b) Average food consumption

Note: In Figure 7a, a deeper shade implies a percentage increase in relative food prices. In Figure 7b, a deeper shade shows a net percentage decline in food consumption levels.

computed with the \(V\text{Rank}\). We notice that the shock has a direct effect on the level of vulnerability of nodes, which steeply increases in particular for the nodes closest to the fault line. In addition, once nodes become vulnerable, this condition is likely to persist even one year after the shock when trade and migration flows have stabilized the markets. The high-density nodes closest to the fault line respond faster to the shock than the low- and mid-density ones. Again, higher density implies that the condition of vulnerability cascades to the neighboring nodes where the response time of low-density nodes is much slower. We notice a stable post-shock distribution of the \(V\text{Rank}\) in the last time steps implying that when the system stabilizes, lower density nodes end up with higher vulnerability and thus higher risk than becoming food insecure.

Our result suggests that the post-shock vulnerability might not be limited to locations near the fault line but could move through the system and persist in locations that are further away from the one hit by the original shock. Our result has important socio-economic implications in the case of climate-led shocks hitting food producing regions. This could be the case of a low-income breadbasket country like Indonesia or India where the effect of the shock could be felt well beyond the country's borders and revive cross-border geopolitical tensions as a consequence of food commodity prices volatility and new migration outflows.

6. Conclusions and research steps ahead

Exogenous shocks, such as climate-led disasters (for example, floods, earthquakes, droughts) could have significant socio-economic impacts along the food trade network that could spread well beyond the originally hit area. Direct and indirect losses are particularly relevant when
Figure 8: VRank percentage change

Note: A deeper shade implies a percentage increase in the VRanks value and thus in vulnerability. The x-axis represents the distance to the fault line where 0 is the shocked region. The y-axis represents the density of nodes, where higher numbers represent more connections.
agrarian, low-income regions are involved. In this case, shocks can impact both the supply side (for example, via disruption of supply networks) and the demand side (via income losses) and migration, eventually triggering cascading indirect losses. These emerge from the complex, spatial-temporal and behavioral interactions of the nodes within heterogeneous layers, where heterogeneous agents responses to the shocks could trigger threshold dynamics resulting in shifting behavioral responses.

There is growing awareness of the fact that traditional economic modeling approaches and network models alone are not able to handle the economic complexity of climate-led shocks. This requires the consideration of the underlying spatial-temporal distributional changes in a socio-economic system that can give rise to system-wide vulnerabilities as well as the complexities in the behavioral response of the system. In this regard, economic complexity-based network model could contribute to understand the patterns and drivers of direct and cascading losses along the network, identifying which nodes are more vulnerable yet relevant for the socio-economic systems exposure to a shock. This information is crucial to inform timely and effective policy response aimed to limit the impact of the shock and avoid a banquet of cascading losses, which could lead to broader socio-economic and geopolitical implications in fragile areas.

By contributing to the economic complexity literature, we introduce a multi-layer behavioral network methodology to analyze the short-term socio-economic impacts of climate-led natural disasters on nodes interconnected in a food trade network. Our methodology allows to account for heterogeneous spatial and temporal preferences, asymmetric information, and path-dependence of policy responses. In addition, it allows us to adopt a modular approach for integrating heterogeneous behavioral response at the level of individual layer in the micro-meso and macro level of analysis. This has several advantages on state of the art modelling, in so far, it allows to, (i) assess the conditions for climate-led natural disasters’ shocks to generate cascade indirect losses via the multi-layer network of agents; (ii) identify the patterns of responses to shocks that are able to trigger a main change in socio-economic conditions (output, price volatility, income inequality), thus including the distributive effects, via cross-sectors feedbacks; (iii) estimate the critical values for which the system reaches tipping points able to lead to fundamental change in the network structure; and (iv) identify the characteristics and conditions for short-term post-disasters policies to foster a resilient network structure that mitigates cascading losses.

We apply the theoretical model to the case of a two-layers (production, household) stylized economy involved in a food production and food trade network, where a node is exposed to the impact of a climate-led disaster. Then, we propose a new multidimensional risk measure, that we call vulnerability rank, $V\text{Rank}$, to quantify the stress in the system following a natural-disaster like scenario.

Our results show that the patterns of results are broken down by temporal and spatial adjustments. Temporal post-shock trends exhibit cyclical vulnerability where the extent of the vulnerability is determined by network configuration. The spatial adjustments show that the distance to the fault line and density of nodes matter in the spatial distribution of shocks. These patterns are analyzed in a model which is fully accommodates displacement and supply chain disruptions. In a real-world setting, where physical and institutional barriers can hinder a full market adjustment, for example through employment and trade restrictions, results are likely to be worse.

Overall, the simulations results show that socio-economic vulnerability to natural disasters is cyclical, and the distribution of shocks depend critically on (i) the network structure, and (ii) on both the speed of supply-side and of the demand-side responses across the network layers.
In particular, we find that pairing the supply-side production networks with the demand-side household network could be crucial to provide a more holistic picture on shock cascades and indirect losses.

Future research steps involve the multi-layer behavioral food trade network model calibration that can be supported by the availability of better quality and higher resolution data. One main example is data provided by the MIT’s Observatory of Economic Complexity on product trade by origin and destination country by year at a highly disaggregated level. This would allow us to assess the role on food trade network shocks of individual food commodities by single breadbasket country. Other examples include the publicly available datasets on natural or made-made shocks related migration and displacement that provide systematically collected information. For instance, EM-DAT, IDMC, and IOM now provide extensive information on various climate-shock related indicators like direct losses and displacement. Additionally, more readily available high-resolution satellite images like the Nightlight data, NASA Earth Observatory, and WorldPop Project allow for the mapping of spatial changes in various socio-economic indicators.

Another area which can help quantify climate shocks are multi-layer risk measures. Multi-layer networks are a relatively new field where recent efforts have focused on establishing new measures (Magnani et al., 2013; Battiston et al., 2014) which range from quantifying network properties, generating a new set of indicators (Gemmetto et al., 2016)) and defining new multi-layer risk measures (Battiston et al., 2012, 2016). These concepts can be easily ported network-based agent-based models and additional multi-layer risk measures can be easily established (GIZ, 2014; Fujii, 2016), for example, by incorporating recently proposed climate shocks-related resilience indicators (Rose, 2004; Birkmann, 2007; Rose, 2007; Parsons et al., 2016).


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