Estimating the Impact of Physical Climate Risks on Firm Defaults: A Supply-Chain Perspective

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Abstract

In this research, an agent-based model was developed to study the propagation of physical climate shocks through supply chain networks. By combining supply chain and financial models, the study examines the effects of climate shocks on firms' production capacities and their subsequent impacts on firm default risk. A comprehensive mathematical framework is presented for the simulation of physical risks, their subsequent up- and downstream impacts along the supply chain, and the translation of physical impacts into an increased level of default risk. The results highlight the importance of supply chains as a transmission channel for physical climate risks and emphasize the effectiveness of implementing adaptation measures. Practical examples demonstrate the model's behavior under different hypothetical climate scenarios and identify the sectors most vulnerable to increases in the frequency and intensity of climate events. Overall, this study provides insights into the transmission dynamics of climate shocks and emphasizes the need for resilience against climate events in supply chain networks.

Keywords: Agent-Based Modelling, Physical Climate Risk, Supply Chain Shock Propagation, Ripple Effect, Default Risk

1 Introduction

As supply chains continue to grow in complexity and global reach, it is becoming increasingly apparent that supply chain disruptions will occur with greater frequency [25] [4]. As such, the scientific community has devoted significant efforts towards modelling the propagation of these disruptions through the supply chain network [9]. The resulting impact of these disruptions is often referred to as the ripple effect, which describes the spread of the disruption and its associated consequences [14]. Other terms used to describe the ripple effect include risk diffusion, cascading failures, and supply chain shock propagation.

Over the past decades, an increasing amount of interest has been given to modelling the impact of climate change. Within the financial industry, the impact of climate change is often separated into two categories: (1) transition risks, which represents the cost for society to transition to a low-carbon economy, and (2) physical risks, which are risks associated to physical climate events. According to the Network for Greening the Financial System (NGFS), these transition and physical risks can induce financial risks through economic transmission channels. One such economic transmission channel is the global supply chain network in which disruptions can cause up- and downstream impacts.

Supply chain disruptions are generally considered to be high-impact, low-frequency events [14]. Consequently, mitigating their impact through the implementation of supply chain resilience measures is of paramount importance. Numerous studies have highlighted the significance of supply chain resilience and the need for effective risk management strategies. This paper contributes to the existing body of work in two ways. First, the paper incorporates the Merton model into an agent-based framework for modelling the ripple effect which allows for default shocks to be modelled. Secondly, the paper investigates the impact of climate-induced physical risks on firms' probability of default under various hypothetical climate change scenarios. The main goal of this research is to introduce a modelling framework to study the propagation of physical climate risks through supply chains.

The paper is organized as follows: the background section provides general information on the ripple effect, the Merton Model, and agent-based modelling. This section is followed by the data section which introduces the data sources that were used to implement the model. Then, the model section provides an in-depth explanation of the agent-based model employed in this study. The results section subsequently discusses the main results from the case study, and finally, the conclusion summarizes the results and provides guidance for future research.

2 Background

2.1 Ripple Effect

The modern economy consists of complex supply chain networks involving multiple stages of production. While such supply chains allow businesses to access a broad range of resources and markets, they are vulnerable to disruptions that propagate throughout the network. Indeed, the interconnectivity and interdependence of components in the supply chain network mean that a disruption in one component can have cascading effects on other components. For example, high-impact-low-frequency events such as certain natural disasters, can disrupt material flows, ultimately affecting the entire supply chain network's functioning [14].

Firms can take various counter-measures to manage the impact of supply chain disruptions. For instance, robustness reserves such as excess inventory and capacity buffers have shown to enhance the resilience of a supply chain [14] . Similarly, information sharing between multiple levels of the supply chain can increase its resilience against disruptions [17]. In addition, the structure of the supply chain network can affect its vulnerability to shocks [16] [18] [4]. For instance, [4] demonstrated that small-world networks perform better than scale-free supply networks and recover more rapidly than both random and scale-free topologies.

Various models have been developed to assess the risk of supply chain disruptions, analyze their interdependencies, and explore their dynamic behavior. A comprehensive review of these models can be found in [9]. One such type of model is the agent-based models. For example, [6] and [5] study the performance of a lube additive firm's supply chain by building a detailed agent-based model consisting of customers, plants, suppliers, and various internal departments. [24] employ an agent-based model on a simple supply chain and investigate the impact of simulated disruptions on the performance of the supply chain. [20] introduces the *Acclimate* model to simulate the propagation of disaster-induced production losses in the global economic network. [16] use an agent-based model to explore the relationship between topological characteristics of complex supply networks and their ability to recover through inventory mitigation and contingent rerouting. [8] combines Monte-Carlo Simulation with Agent-Based Modeling to quantify the degree of vulnerability and criticality of entities in a real, complex supply network. [4] introduces the MTG model, inspired on epidemiological research, to examine the impact of global supply network structure on risk diffusion and supply network health and demonstrate the importance of supply network visibility. [18] builds on top of the MTG model, and uses various simulations to explore the resilience of supply chains in the presence of the ripple effect. Finally, [17] investigates the impact of information sharing in a three-echelon supply chain using an agent-based model.

2.2 Merton Model

The Merton model is a widely used model for predicting the likelihood of default by firms [23]. The model is based on the assumption that a firm's value can be modeled as a function of its assets and liabilities, and that default occurs when a firm's liabilities exceed the value of its assets [19]. The Merton model uses a continuous-time framework and assumes that the value of a firm's assets follows a geometric Brownian motion

$$dV = \mu V dt + \sigma_V V dW \tag{1}$$

where V is the total value of the firm, μ is the expected continuously compounded return on V , σ_V is the volatility of the firm value and W is a standard Wiener process. Furthermore, the initial Merton model assumes that a firm's debt corresponds to the issue of a single bond with maturity T, which means that the firm's equity can be modeled as a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt and a time-to-maturity of T. Based on these assumptions, the equity value of a firm satisfies the Black-Scholes equation: [19]

$$E = VN(d_1) - e^{-rT} FN(d_2) \tag{2}$$

with E the market value of a firm's equity, F the face value of the firm's debt, $N(.)$ the cumulative distribution function of the standard normal distribution, r the risk free rate, [19]

$$d_1 = \frac{\ln(\frac{V}{F}) + (r + \frac{1}{2}\sigma_V^2)T}{\sigma_V \sqrt{T}} \tag{3}$$

and $d_2 = d_1 - \sigma_V \sqrt{T}$. Furthermore, it can be shown that the equity and asset value volatility are linked based on [7]

$$\sigma_E = \left(\frac{V}{E}\right) N(d_1)\sigma_V \tag{4}$$

The parameters σ_E and F can be estimated directly by respectively using historical returns data and taking the firm's total liabilities as the face value of the firm's debt. Also, data can be obtained for the risk-free rate and the market equity of the firm. The problem however is that the values for V and σ_V cannot be observed.

[7] provide an iterative algorithm to obtain values for V and σ_V based on simultaneously solving equations 2 and 4.

Based on the results above, the default probability can be determined in multiple ways. The KMV model, a commonly used implementation of the Merton Model, defines the probability of default as the probability that the asset value is below the face value of company debt at maturity [12], i.e.,

$$P(Default) = P(V_T < F) = N\left(-\frac{\ln(\frac{V}{F}) + (\mu - \frac{1}{2}\sigma_V^2)T}{\sigma_V\sqrt{T}}\right) \tag{5}$$

The disadvantage of this method is that firms are only allowed to default at maturity. Alternatively, the barrier version of the Merton model can be used. In this case, the firm defaults whenever the asset value drops below the face value of company debt at any point in time up to maturity [3]. In this case, the probability of default is given by

$$P(Default) = N\Big(-\frac{\ln(\frac{V}{F}) + (r - \frac{\sigma_V^2}{2})T}{\sigma_V\sqrt{T}}\Big) + \Big(\frac{V}{F}\Big)^{1-\frac{2r}{\sigma_V^2}} \times N\Big(\frac{\ln(\frac{F}{V}) + (r - \frac{\sigma_V^2}{2})T}{\sigma_V\sqrt{T}}\Big) \tag{6}$$

An additional extension of the traditional Merton model is the Merton Jump Diffusion Model, in which the asset value process also incorporates jump dynamics, i.e

$$dV_t = \mu V_t dt + \sigma_V V dW_t + V_{t^-} dQ_t,$$

where $Q_t = \sum_{i=1}^{N(t)} Y_i$ is a compound Poisson process, $N(t)$ is a Poisson process with intensity λ, the jumps Y_i are i.i.d random variables and $V_{t^-} = \lim_{s \uparrow t} V_s$ is the left limit [21] [28]. Analytical approximations for the probability of default are provided in [28].

2.3 Agent-Based Modelling

Agent-based modelling (ABM) is a computational modelling technique that has gained popularity in a range of fields including economics [26], and finance [11]. The technique is used to understand complex phenomena that emerge from the interactions of multiple agents, each with their own behavioral rules, decision-making processes, and learning mechanisms. The key idea behind ABM is to simulate the behavior of individual agents and their interactions within an environment [5], and to observe the emergent patterns that result from the collective behavior of the agents [10].

It is particularly well-suited to modelling systems with heterogeneous agents, where individual agents have different attributes, preferences, and decision-making mechanisms. ABMs are typically built using a bottom-up approach, starting with simple rules and assumptions that govern the behavior of individual agents, and gradually building up to more complex interactions and emergent phenomena.

There are a number of advantages to using ABM over other modeling techniques. For example, it allows researchers to study the behavior of complex systems in a way that is more flexible and realistic than traditional models. ABM also allows for the incorporation of rich, heterogeneous data, and can capture the effects of feedback loops, non-linear dynamics, and other complex phenomena that may be difficult to capture using other modeling techniques.

However, there are also some limitations. One of the challenges in ABM is selecting appropriate rules and parameters for individual agents that accurately reflect their behavior in the real world. ABM models can also be computationally intensive, particularly for large-scale simulations with many agents and complex interactions. Nevertheless, ABM has proven to be a valuable tool for exploring complex systems, and has led to many new insights in a range of fields.

3 Data

The model, which will be presented in section 4, requires a variety of data sources. First, the model requires information about each firm that will be included in the analysis. This information includes a complete overview of the supply chain of the company, as well as information on financial metrics. This firm-level data is obtained through FactSet. Specifically, the FactSet supply chain database was used to obtain supply chain information of firms. Besides relationships between firms, this database also contains an indication of the importance of the relationship represented as a percentage of revenue of the supplier that depends on the relationship. For example, a size of 5% indicates that 5% of the revenue of the supplier depends on the relation. The financial information of firms consists of both fundamental data (ratios) as well as price histories of financial assets which are used for the calibration of the Merton model. Because not all firms have these types of information available, sector averages are used to fill in data gaps.

Secondly, data on the frequency and intensity of natural disasters is needed to simulate the environment in which the firms operate. This data is collected from the EM-DAT (Emergency Events Database) and the Our World in Data platform [22]. EM-DAT is a global database on natural and technological disasters, containing essential core data on the occurrence and effects of more than 21,000 disasters in the world, from 1900 to the present. The database is maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the School of Public Health of the Université catholique de Louvain [1].

In the results section, the behavior of the model will be shown based on the application of the model on a large network of firms. This network consists of 5 236 firms that have a total of 7 681 relationships between them. The firms included in the analysis belong either to the S&P 500 directly, or are an important supply chain partner of any of the firms belonging to the S&P 500. A visual representation of the network is provided in figure 1.

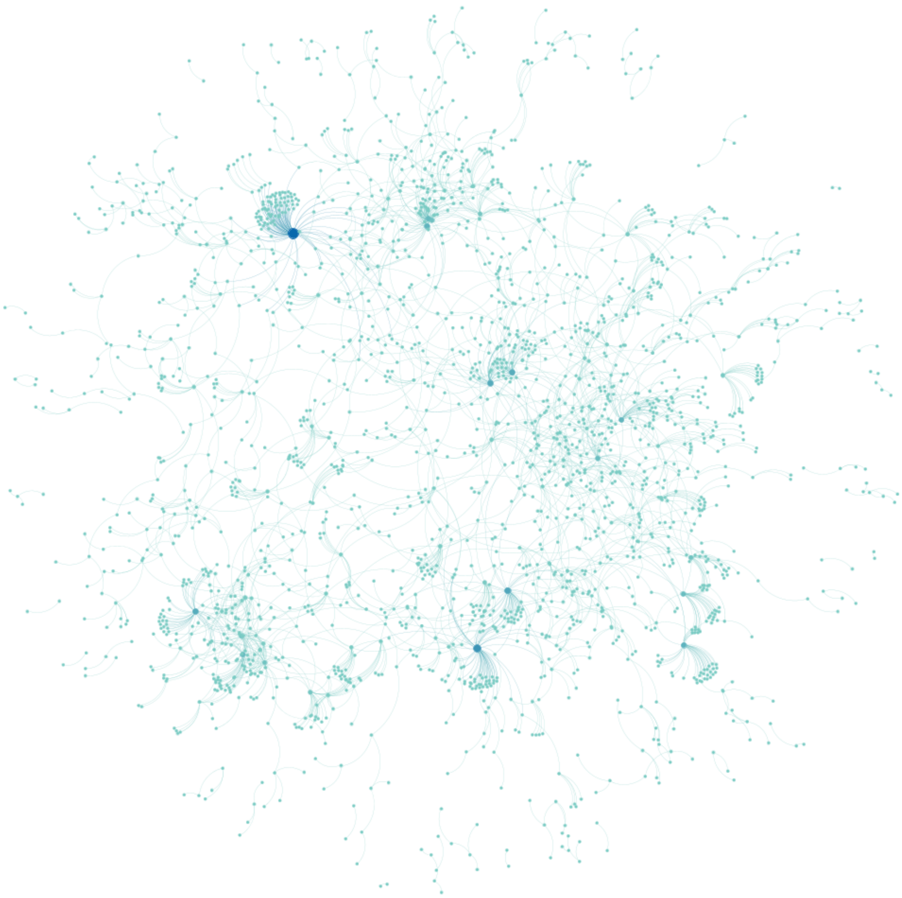

Figure 1: A visual representation of the network used in the discussion of the results.

4 Model

The proposed agent-based model consists of three parts: (1) the agents, which represent real-life firms and their production facilities, (2) the shocks, which are modelled based on real-life climate data, and (3) the simulation that determines the order in which events take place. In this section, the different parts of the agent-based model will be discussed in depth.

4.1 Agents

The model's agents are representative of actual firms, where each firm consists of one or more production facilities and is connected to a network of suppliers and customers. The agents' behavior is modelled according to the real-life processes of firms.

Production The firms' production is based on fixed input recipes, wherein substitution is not possible. The production schedule of the firms is based on the projected demand, the combined maximum capacity of the production facilities, and possible input bottlenecks. Firms use exponential smoothing to obtain the projected demands based on their past production and demand levels. The smoothing parameter was set equal to 0.2. Based on the remaining capacity of each production facility, the firm will determine how it will divide its scheduled production over the different production facilities. The actual production process takes place at these production facilities. The duration of production is modelled using a uniform distribution over a range of 1 to 3 days. The finished goods are stored in the final goods inventory and can be accessed immediately to fulfill customer orders.

Inventory Keeping excess inventory is an effective strategy to mitigate the effects of supply chain disruptions on a firm's operations. Indeed, extensive research has demonstrated that higher levels of excess inventory can enhance supply chain resilience [14]. The implemented model includes two types of inventories: input inventories, which store the necessary inputs for production and are located at production facilities, and finished goods inventories, which hold products ready to be dispatched to customers. The desired level of input inventories corresponds to the inputs required to produce five times the average number of goods demanded in the network's equilibrium state. Furthermore, the agents aim to keep the finished goods inventory as close as possible to five times the average demand for goods in the network's equilibrium state, with the inventory size restricted to ten times the equilibrium demand. Any production that exceeds the prescribed inventory limit is discarded. There are no costs associated to holding inventories.

Demand The demand for each firm's products consists of two components: (1) the demand by other firms, which use the output of the firm as an input in their production recipes, and (2) the consumer demand. Initial demand and production levels are calibrated using data collected from the FactSet Supply Chain Database combined with reported revenue data. The first type of demand is handled by the model using an order system. Each production facility manages its own orders based on a fixed reorder point policy on its input inventories. Orders can have three states: (1) processing, meaning that the order has been sent to the supplier, (2) dispatched, meaning that the order is currently in transit, and (3) fulfilled, meaning that the goods have been received. Orders are fulfilled based on a first-come, first-serve basis, and transit times are uniformly distributed over a range of 1 to 3 days. The consumer demand is normally distributed with a volatility of 3% of the equilibrium final demand. In case the total demand cannot be fulfilled, a proportional split is made between the consumer demand and the demand by other firms. Unfulfilled consumer demand will be put in a backlog; however, customer churning is implemented to avoid the consumer backlog from growing indefinitely.

4.2 Shocks

The agents in the model are exposed to two types of shocks: (1) Exogenous shocks that represent real-life environmental disasters like floods, storms, extreme temperatures, droughts, and wildfires, and (2) default shocks that are caused by defaults within the supply chain network which cause reduced demand at their suppliers, and input bottlenecks at their customers. Exogenous climate shocks can trigger default shocks. The intensity of the shock represents the proportion of lost production capacity at the impacted facilities. The recovery of the production facilities are modelled using a linear recovery function in which the simulated shock duration represents the time it takes to reach full recovery. For example, a shock with intensity and duration equal to 0.5 and 15, represents a loss of 50% of the production capacity of the impacted facilities that will only be completely recovered after 15 business days.

4.2.1 Simulating Natural Disasters

The exogenous shocks that represent real-world natural disasters are simulated using a compound non-homogeneous Poisson process in which the frequency, economic impact, and duration of the shock are modelled based on real-world data. Furthermore, interactions between different climate events are modelled using a Hawkes process. As mentioned above, data on the frequencies and impact of natural disasters are collected from EM-DAT and Our World in Data.

Modelling the impact and duration of climate shocks Both the economic impact and the duration of the shock are modelled using a bounded (truncated) Pareto distribution

$$f(x) = \frac{\alpha L^{\alpha} x^{-\alpha-1}}{1 - \left(\frac{L}{H}\right)^{\alpha}}, \tag{7}$$

where $L \leq x \leq H$, and $\alpha > 0$. The economic impact of a climate shock is bounded between 0.01 and 1, and represents the proportional reduction in the capacity of the impacted production facilities. The scale parameter α is estimated based on the historic proportional reductions in 1-day GDP due to climate events. This estimate corresponds to the Maximum Likelihood Estimate provided by [2] which satisfies

$$\frac{n}{\tilde{\alpha}} + \frac{n(\frac{L}{U})^{\tilde{\alpha}} \ln(\frac{L}{U})}{1 - (\frac{L}{U})^{\tilde{\alpha}}} - \sum_{i=1}^{n} \left[\ln X_{(i)} - \ln L \right] = 0 \tag{8}$$

with n being the number of events in our dataset. The scale parameter is estimated for each country and climate event type (i.e., flood, storm, extreme temperature, drought, and wildfire). Figure 5 provides an example of the estimated distributions for floods in Belgium under various climate scenarios. The scale parameter for the duration of the shock has been set equal to 5, and the lower and upper limits are equal to 5 and 20.

The dependence between the duration and economic impact of climate shocks is modelled using a Joe copula [27]

$$C(u_1, \dots, u_n) = 1 - (1 - [1 - (1 - u_1)^{\alpha}] \times \dots \times [1 - (1 - u_n)^{\alpha}])^{\frac{1}{\alpha}}. \tag{9}$$

These copulas are part of the class of Archimedean copulas, with generator

$$\phi(t, \theta) = -\ln\left(1 - (1 - t)^{\theta}\right). \tag{10}$$

The advantage of using a Joe copula is that they have non-zero upper tail dependence

$$\lambda_U = \lim_{t \to 1^-} P\left(Y > F_Y^{-1}(t) \mid X > F_X^{-1}(t)\right) = 2 - 2^{\frac{1}{\theta}}, \tag{11}$$

which corresponds with the observation that climate events with large economic impacts tend to have longer durations.

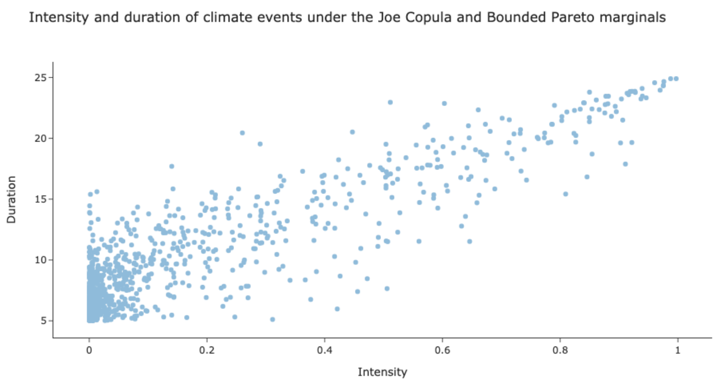

Figure 2: Example of a simulation of climate events using the bounded Pareto distribution as marginal distributions, and the Joe copula to model the dependence between the economic impact and duration. The figure shows how climate events with high economic impacts typically have longer durations.

The economic impact and duration of climate events are therefore simulated by generating two random numbers making use of the Joe copula. The inverse-transform method, shown in equation 12, is then used to generate values for the economic impact and duration of climate shocks following the bounded Pareto distribution

$$x = \left(- \frac{UH^\alpha - UL^\alpha - H^\alpha}{H^\alpha L^\alpha} \right)^{-\frac{1}{\alpha}}. \tag{12}$$

Modelling the occurrence of natural disasters In order to model the arrival of climate events, a model needs to be used that takes into account the seasonality of climate events as well as the interactions between different climate events. For example, extended periods of drought increase the likelihood of a subsequent forest fire [**?**]. Therefore, a distinction is made between two classes of events: source events and subjugate events. The occurrence of a source event increases the rate at which their related subjugate events occur. The events that are modelled in this study are droughts, extreme temperatures, floods, storms, and wildfires. There are two interactions that are modelled (see table 1):

Source event	Subjugate event	Alpha
Drought	Wildfire	0.0068
Storm	Flood	0.0023

Table 1: The interactions between climate events included in this study.

Source events, and events not included in table 1, are modeled using a non-homogeneous Poisson process whose arrival rate is estimated using historical data from the Our World In Data database. Concretely, we have that the arrival rate $\lambda(t)$ for business day t occurring in month i is given by

$$\lambda(t) = \frac{\text{Number of events in month } i}{\text{Length of month } i \times \text{Number of years in data set}}. \tag{13}$$

As an example, the estimated arrival rates of storms in China, the Phillipines and Australia are shown in figure 3.

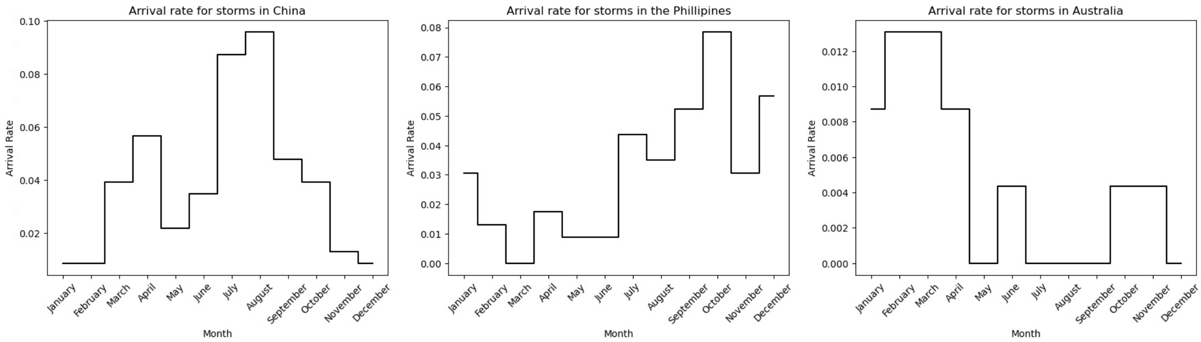

Figure 3: Estimated arrival rates for a selection of countries. These arrival rates determine the frequency of simulated events in the homogeneous poisson process.

Subjugate events are modelled using a Hawkes process. In a Hawkes process, the expected frequency of subjugate events is temporarily increased (decreased) as a result from a source event. Denoting by N_t the counting process associated to the subjugate events and $\tilde{N}_t$ for the source events, the following rate function is used:

$$\lambda(t) = \lambda^{\text{BG}}(t) + \int_0^{+\infty} \phi(t-s) d\tilde{N}_s \tag{14}$$

The term $\lambda^{\text{BG}}(t)$ (*background* λ) corresponds to the arrival rate without the occurrence of a source event. The increase of the arrival rate due to the occurrence of a source event is modelled in the kernel function ϕ. For simplicity, the indicator function was used:

$$\phi(x) = \alpha \cdot \mathrm{I}_{\{0 \leq x \leq 22\}} \tag{15}$$

The model assumes that for each occurrence of the source event, the arrival rates of the subjugate events increase by α for the next 22 business days

$$\lambda(t) = \lambda^{\text{BG}}(t) + \alpha \cdot [\tilde{N}_t - \tilde{N}_{t-22}] \tag{16}$$

The parameter α is estimated using historical data (see table 1). Then, the value of $\lambda^{\mathrm{BG}}(t)$ is determined by ensuring that $\lambda(t)$ corresponds to the observed arrival rate in our data. As an example for the calibration of the parameters, the cumulative arrival rate of floods in the USA are provided in figure 4:

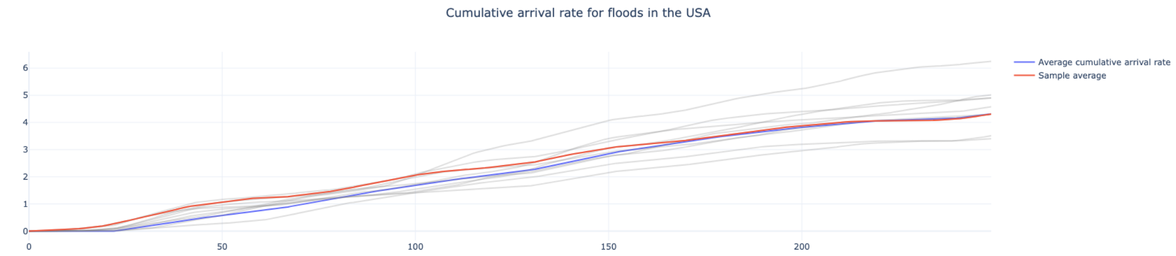

Figure 4: Realizations of the cumulative arrival rate $\Lambda(t)$ for storms in the United States of America compared to the sample average. The figure shows that on average, the estimated model closely follows the patterns observed in the data.

Even though the modelling of interactions using a Hawkes process does not impact the total number of subjugate events or the intensity of these events, it results in source events and subjugate events that tend to cluster. The occurrence of events in clusters gives impacted firms less time to recover and ultimately increases their probability of default in the model.

Modelling hypothetical climate scenarios In this study, two parameters are used to develop hypothetical climate scenarios. First, a frequency multiplier is used to model the increased (decreased) frequency of climate shocks experienced by firms. Secondly, an intensity multiplier represents the increase (decrease) in economic damage induced by each individual climate shock. All hypothetical climate scenarios are defined relative to the *current world scenario* which corresponds to the model with parameters fitted based on the data sources mentioned above.

The increase in frequency of climate events is taken into account by multiplying the frequency $\lambda(t)$ (see equations 13, 16) of the events by the scaling factor. For example, a scaling factor of 1.2 for the droughts event indicates that in the hypothetical climate scenario the number of droughts is expected to increase by 20%. The scaling factor is specified for each climate event type individually.

For the economic damage of climate events, the scaling factor (α) of the country and climate event is updated such that the mean of the impact distribution (equation 17) is scaled according to the intensity multiplier (see Figure 4). For example, a scaling factor for the intensity of storms in the United States equal to 1.3 indicates that the average economic impact of individual storms is expected to increase by 30% in the hypothetical climate scenario. Modifying the scale parameter to match the expected average economic impact has the additional effect of increasing the size of the tails of the distributions (see equation 11 and Figure 5).

$$\bar{x} = \frac{L^{\alpha}}{1-\left(\frac{L}{H}\right)^{\alpha}} \times \left(\frac{\alpha}{\alpha-1}\right) \times \left(\frac{1}{L^{\alpha-1}} - \frac{1}{H^{\alpha-1}}\right) \tag{17}$$

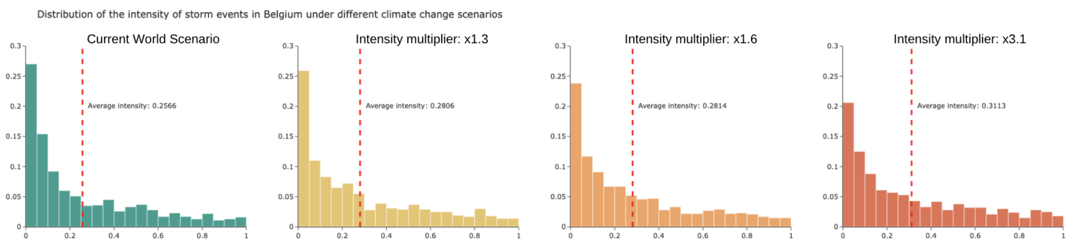

Figure 5: To modify the distribution of economic damages induced by a climate shock, the scale parameter is adjusted such that the newly obtained average intensity is equal to the original intensity in the *Current World* multiplied by the intensity multiplier. The figures above show how the distribution of the intensity of storm events in Belgium under intensity multipliers equal to x1.3, x1.6, and x3.1.

4.2.2 Default shocks

Firms are also impacted by defaults of suppliers or clients. Indeed, a defaulting client will reduce the demand for the firm's products, and a defaulting supplier will impact the production of the firm. The agent-based model uses a jump-diffusion Merton Model to model these firm defaults. In summary, the Merton model uses a stochastic model to represent the firm's asset value over time. When the asset value drops below a certain barrier, the firm will be considered to have defaulted.

In this study, the asset values are modeled using a jump-diffusion process. The volatility of the jump-diffusion process is computed based on the iterative procedure discussed in [7]. The jumps of the process correspond to the supply chain shocks. Three types of supply chain shocks are modelled: (1) a reduction in the production capacity of firms which leads to the firm being unable to deliver the amount of goods demanded by their clients, (2) a lack of available inputs to produce the required number of goods to satisfy demand (upstream shock), and (3) a reduction in demand resulting in a loss of sales (downstream shock).

Whenever any of the aforementioned shocks occur, a shock proportional to the lost production or sales will be applied to the asset values. The size of the shock on the asset values is equal to the proportional loss of production divided by the firm's Enterprise Value to Sales ratio (EV/S ratio). The EV/S ratio is estimated based on sector averages. Negative shocks, that reduce the probability of default of a firm, are also possible because firms can use their excess capacity to temporarily increase production levels thereby increasing their sales. This scenario typically occurs when a firm has just recovered from a climate shock. Indeed, in this case, not all customers will have churned and the firm will be able to recover some of their lost sales.

The implementation of the Merton model follows the barrier-option framework as discussed in [3] which allows a firm to default at any point in time, whenever its asset value drops below a certain barrier. The default barrier is calibrated based on a firm's credit rating which has a corresponding observed probability of default [15]. Since the frequency and intensity of the jumps are determined based on the supply chain network, there is no analytical solution that can be used to obtain this barrier. In this model, the barriers are set using equation 6, but it is recognized that this results in slightly too many defaults that occur in the simulations.

Firm defaults are modelled as production shocks equal to 100% of the production capacity of all facilities with a sudden recovery after 10 business days. This setting resembles the process of a firm having to find a new supplier and/or customer. Whenever a firm is recovered from its default, the asset values are reset to their starting point.

4.3 Simulations

Each simulation consists of 250 progressions that correspond to a single business day. The assumption is made that one calendar year corresponds to 250 business days. A warm start of 50 iterations without any shocks is used to ensure that the network is stable when the simulation of interest starts. Each iteration consists of a sequence of steps that largely follows the procedure by [24]:

1. Forecast demand: each firm forecasts the demand they expect to have during the current iteration;
2. Receive goods: the facilities receive and process goods that arrived from suppliers;
3. Explode demand: the facilities determine how much inputs they need to produce their desired output;
4. Produce goods: inputs are used and transformed into final goods based on a production schedule;
5. Put goods to stock: the goods that are ready are transferred to the final stock;
6. Affirm need: the firms check how much demand is currently outstanding and fulfill as many orders and consumer demand as possible;
7. Apply Shock: Checks whether a shock is applied to the production facilities, and whether certain facilities are recovering from shocks;
8. Check default: checks whether the firm defaults at the end of the day. Also generates the asset value during the next iteration based on a random number generator and the firm's production level.

A total of 200 simulations is used for each hypothetical climate scenario.

5 Results

The model described above can be used to estimate the sensitivity of firm defaults under increases (decreases) in the frequency of natural disasters and their associated economic damages. The first section of the results discusses the application of the model in a selection of hypothetical climate scenarios. The second section discusses the sensitivity of firm defaults to marginal increases (decreases) in the frequency and economic impact of each individual disaster type.

5.1 Scenario Analysis

Table 2 and 3 provide an overview of the intensity and frequency multipliers used in the climate scenarios. An intensity multiplier equal to $\times 1.5$ indicates that the average economic impact of climate events is increased by 50% compared to the *current world scenario*. A frequency multiplier equal to $\times 1.5$ indicates the climate events' expected frequency is equal to 1.5 times the frequency in the *current world scenario*. Like mentioned above, both the economic impact and the frequency of climate events in the *current world scenario* are defined for each individual country and are estimated based on historic data.

Extreme Event	Current World	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Droughts	$\times 1$	$\times 1.5$	$\times 3$	$\times 1.5$	$\times 0.7$
Extreme Temperatures	$\times 1$	$\times 5$	$\times 10$	$\times 5$	$\times 0.5$
Floods	$\times 1$	$\times 1.5$	$\times 1.5$	$\times 1.5$	$\times 0.8$
Storms	$\times 1$	$\times 1.5$	$\times 3$	$\times 1.5$	$\times 0.75$
Wildfires	$\times 1$	$\times 1.5$	$\times 2.5$	$\times 1,5$	$\times 0.5$

Table 2: Increase in frequency of extreme weather events for the different scenarios.

Extreme Event	Current World	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Droughts	$\times 1$	$\times 1.25$	$\times 2.5$	$\times 0.75$	$\times 0.75$
Extreme Temperatures	$\times 1$	$\times 1.1$	$\times 1.25$	$\times 0.9$	$\times 0.9$
Floods	$\times 1$	$\times 1$	$\times 1$	$\times 0.75$	$\times 0.75$
Storms	$\times 1$	$\times 1.075$	$\times 1.25$	$\times 0.8$	$\times 0.8$
Wildfires	$\times 1$	$\times 1.25$	$\times 1.75$	$\times 0.6$	$\times 0.6$

Table 3: Increase in economic impact of extreme weather events for the different scenarios.

The scenario parameters have been chosen to highlight the behavior of the model under a wide variety of climate parameters. *Scenario 1* corresponds to a moderate increase in both the impact and frequency of climate events, whereas *scenario 2* should represent an extreme scenario with severe increases in both the frequencies and impacts. *Scenario 3* on the other hand represents a scenario in which there is a moderate increase in the frequency of extreme events, but a moderate decrease in the impact of these events (e.g., thanks to adaptation measures taken by firms). Finally, *scenario 4* indicates a scenario where both the frequency and impact of natural disasters decreases.

5.1.1 Impact on firm defaults

The metric of interest for these climate scenarios is the increase in median default probability of the firms. The baseline metric for this increase is the default probability in the current world scenario. Bootstrapping is used to obtain an interval estimate of this increase. Bootstrapping is a data resampling technique that provides parameter estimates without assuming a specific probability density function [13].

Scenario	Point estimate	Confidence interval (90%)	Skew (statistic)	Skew p-value
Current world	-	-	4.61	0.0000
Scenario 1	13.33%	[10.0%, 16.96%]	4.51	0.0000
Scenario 2	43.32%	[39.23%, 45.99%]	1.71	0.0871
Scenario 3	1.04%	[-2.38%, 5.52%]	3.37	0.0008
Scenario 4	-20.85%	[-23.45%, 16.31%]	4.39	0.0000

Table 4: The estimated increases in median the default probability under the various scenarios, represented as a proportional increase compared to the *current world scenario*. The confidence interval is obtained through bootstrapping. The final columns also indicate the skewness of the average default probability over the different simulations.

Table 4 shows the increases (decreases) in the median default probability under the hypothetical climate scenarios. The largest increase in default probability is observed in *scenario 2* which represents an extreme increase in the frequency and intensity of climate impacts. A comparison between the results of *scenario 1* and *scenario 2* indicates that more extreme and frequent climate impacts results in an increase in the number of defaults. Furthermore, in *Scenario 4*, which represents a decrease in the frequency and intensity of climate events, fewer firms defaulted in the simulation. *Scenario 3* which represents a decrease in the economic impact of climate events compared to *scenario 1*, shows how the implementation of adaptation measures, i.e., a reduction in the economic impact of climate events, can offset the negative effects associated with the increase in the frequency of these climate events.

Finally, the skewness of the number of defaults across the simulations is also investigated. This skewness is a measure of the assymmetry of a distribution and indicates whether a distribution has 'heavy' tails. The results, provided in table 4, suggest that the number of defaults across the simulations follows a right-skewed distribution.

5.1.2 Impact on sectors

Firms that operate in different sectors typically have different supply chain structures and financial characteristics. These things influence the sensitivity of the sectors to the impact of climate events. By comparing the results of *scenario 1*, a moderate increase in the impact and frequency of climate events, an analysis can be made of which sectors are most vulnerable. Figure 6 provides an overview of the results for both scenarios. The sectors that, according to the model, are most vulnerable to increases in the frequency and intensity of climate events are: (1) transportation, (2) utilities, (3) commercial services, (4) retail trade, and (5) industrial services. The sectors that are least affected b climate change are: (1) communications, (2) technology services, (3) finance, (4) consumer services and (5) consumer non-durables.

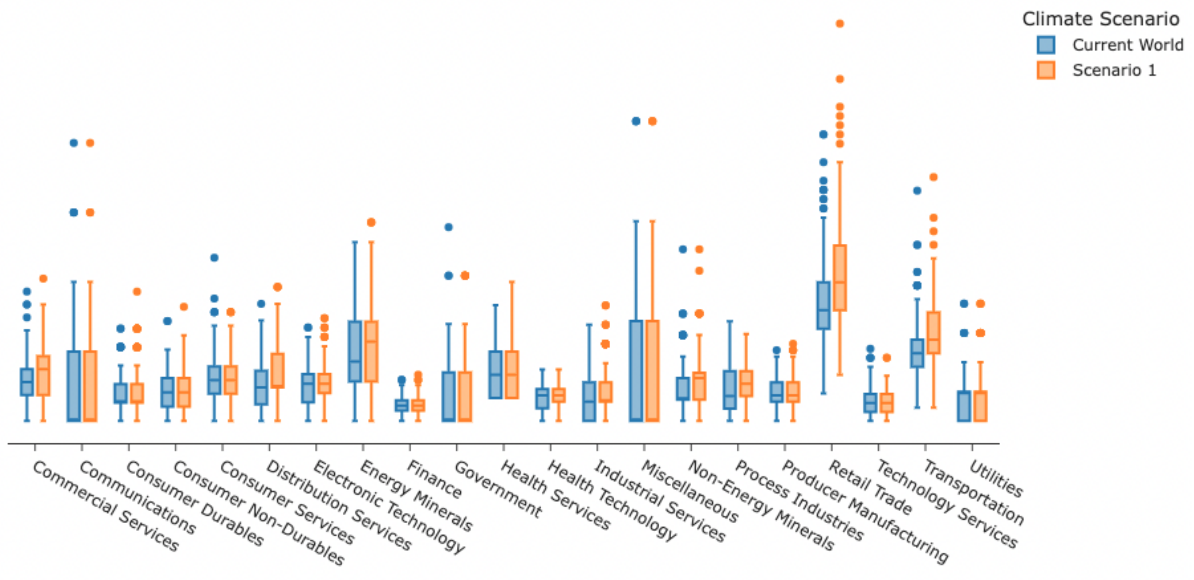

Figure 6: Sector-level results of the *current world scenario* and *scenario 1* indicating how, according to the model, different sectors are differently impacted.

5.2 Sensitivity Analysis

In this section, the marginal impact of an increase (decrease) in the frequency or economic impact of natural disasters is investigated. This analysis is done using the technique of sensitivity analysis. In sensitivity analysis, the model parameters are increased (decreased) individually and the resulting impact of these increases (decreases) is investigated.

The impact of increasing frequencies of climate events The model can be used to investigate the impact of an increase in the frequency of different types of climate events on the number of firm defaults. In this analysis, simulations are performed where each disaster type's frequency was doubled keeping the frequencies and intensities of other disaster types constant. The disaster type with the greatest impact on the average number of defaulted firms is the *storm* type (+16.1%), followed by the *flood* (+13.4%), *drought* (+7.9%), and *wildfire* (+5.6%) disaster types. The sensitivity of the firm defaults to a doubled number of extreme weather events is limited to 0.6%.

The mitigating impact of adaptation measures Adaptation measures can be represented in the model as a reduction in the economic impact of climate shocks. Indeed, the implementation of adaptation measures will reduce the vulnerability of firms to climate events, therefore limiting the impact of these shocks on their production processes. To assess the model's sensitivity to reductions in the impact of climate events, a sensitivity analysis was conducted in which the economic impact of each individual climate shocks was halved keeping all other parameters constant. Based on the model, adaptation measures are most effective when taken against storms (-16.89%), followed by droughts (-2.6%), floods (-2.2%), wildfires (-1.1%). There is no difference for extreme temperatures.

6 Conclusion

In this research, an agent-based model was developed to study the propagation of physical climate shocks through supply chain networks by combining models from the supply chain literature with financial models. The firms in the agent-based model are exposed to climate shocks which affect their production capacities. These reductions in production capacities subsequently lead to up- and downstream impacts through the supply chain. Indeed, suppliers of the affected firms are faced with lower demand, and clients of the affected firms could be required to reduce their own production levels due to input bottlenecks.

Two practical examples of the implementation of the model were provided in the results section. First, various hypothetical climate scenarios were used to show the overall behavior of the model. These scenarios highlighted that increases in the frequency or intensity of climate events have a substantial impact on the number of firm defaults in the model. Furthermore, a reduction in the economic impact of climate shocks, which could correspond to the implementation of adaptation measures, results in a substantial reduction in the number of defaults. These results show the importance of supply chains as a transmission channel of physical climate risks and highlight the usefulness of the implementation of adaptation measures to reduce the impact of climate events. The results also show a large difference between the impacts across different sectors. Certain industries like transportation, utilities, and commercial services experienced large increases in the number of defaults due to a modest increase in the frequency and intensity of climate events, whereas other industries, like communications, technology services, and finance where hardly impacted.

Secondly, sensitivity analysis was used to detect which climate event types have the largest impact on the number of defaults in the simulation, and which adaptation measures should be prioritised to reduce the amount of defaults. The disaster type *storm* was shown to have the largest impact. If the amount of storms would double, the model estimates an increase of 16.1% in the number of defaults. A doubling of the frequency of floods and droughts has a respective increase of 13.4% and 7.9% in the number of defaults in the simulation. According to the model, adaptation measures that reduce the impact of storms are most effective in mitigating the overall impact of climate events on firm defaults (-16.9%). The second and third most effective adaptation measures manage the exposure to droughts (-2.6%) and floods (-2.2%).

Overall, the study highlights the importance of the supply chain network as a transmission channel of physical climate risks. A comprehensive mathematical framework for modelling these physical risks has been introduced that includes the modelling of climate shocks using a non-homogeneous poisson process in conjunction with a Hawkes process to model the interactions between climate events. Furthermore, the model provides up- and downstream mechanisms for the propagation of climate shocks and translates these shocks into an increased risk of firm default. The results show that this modelling framework is consistent with the expectation that increases in frequencies and intensities lead to an increased number of defaults in the simulations.

6.1 Limitations and further research

There are important limitations to the study. First and foremost, agent-based models are developed using a bottom-up approach in which the underlying processes of agents and their interactions are modelled and simulations are used to study the behavior of this model. An important limitation of this approach is that it is difficult to verify how accurate the model is. Many assumptions need to be made in order to develop a practical implementation of such models and it is unclear how these assumptions affect the conclusions that are drawn. Nonetheless, agent-based models have been proven to be a valuable tool in a variety of fields. Compared to other commonly used methods, these agent-based models are a powerful and flexible technique for modelling complex problems. Secondly, the model still suffers from a lack of data availability with respect to firm-specific information. Indeed, there are important differences between the vulnerability of individual firms to certain climate shock but unfortunately there is no sufficiently granular data available at the time of this analysis. Furthermore, the climate shocks are currently defined at the country-level where a firm is affected by each shock in the country. In practise firms can have production facilities spread across the globe, but this is not taken into account in the current implementation due to a lack of data on the specific geographic locations of company facilities.

Future studies can address these problems. First, researchers can focus on the development of alternative models to investigate the importance of supply chains as a transmission channel for physical climate risks. These models can use data-driven techniques or follow a similar bottom-up approach as presented in this study. The stability of the results with respect to different model decisions (inventory policies, default models, climate models etc.) should also be investigated. Secondly, there are many other possible applications for agent-based models in the study of climate risk. This research focused specifically on physical climate risks even though various types of transition risks can be modelled in the same framework. For example, shifts in consumer preferences are a potential demand shock that can be introduced. Another example is the study of the impact of carbon taxes across supply chains which would require the incorporation of monetary flows into the current modelling framework.

References

[1] EM-DAT | The international disasters database.

[2] Inmaculada B Aban, Mark M Meerschaert, and Anna K Panorska. Parameter Estimation for the Truncated Pareto Distribution. *Journal of the American Statistical Association*, 101(473):270–277, March 2006. Publisher: Taylor & Francis _eprint: https://doi.org/10.1198/016214505000000411.

[3] Petra Andrlikova. Is Barrier version of Merton model more realistic? Evidence from Europe. *Proceedings of International Academic Conferences*, October 2014. Number: 0801868 Publisher: International Institute of Social and Economic Sciences.

[4] Rahul C. Basole and Marcus A. Bellamy. Supply Network Structure, Visibility, and Risk Diffusion: A Computational Approach. *Decision Sciences*, 45(4):753–789, 2014. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/deci.12099.

[5] Behzad Behdani, Arief Adhitya, Zofia Lukszo, and Rajagopalan Srinivasan. Mitigating Supply Disruption for a Global Chemical Supply Chain-Application of Agent-based Modeling. In Iftekhar A. Karimi and Rajagopalan Srinivasan, editors, *Computer Aided Chemical Engineering*, volume 31 of *11 International Symposium on Process Systems Engineering*, pages 1070–1074. Elsevier, January 2012.

[6] Behzad Behdani, Zofia Lukszo, Arief Adhitya, and Rajagopalan Srinivasan. Performance analysis of a multiplant specialty chemical manufacturing enterprise using an agent-based model. *Computers & Chemical Engineering*, 34(5):793–801, May 2010.

[7] Sreedhar T. Bharath and Tyler Shumway. Forecasting Default with the Merton Distance to Default Model. *The Review of Financial Studies*, 21(3):1339–1369, May 2008.

[8] Niels Bugert. Risk Budget Planning through Assessing the Criticality and Vulnerability of Supply Network Entities Facing Disruption Risks. *IFAC-PapersOnLine*, 52(13):1295–1300, January 2019.

[9] Niels Bugert and Rainer Lasch. Supply chain disruption models: A critical review. *Logistics Research*, 11(5):1–35, 2018. Publisher: Bremen: Bundesvereinigung Logistik (BVL).

[10] Wai Kin Victor Chan, Young-Jun Son, and Charles M. Macal. Agent-based simulation tutorial - simulation of emergent behavior and differences between agent-based simulation and discrete-event simulation. In *Proceedings of the 2010 Winter Simulation Conference*, pages 135–150, December 2010. ISSN: 1558-4305.

[11] Ting-Ting Chen, Bo Zheng, Yan Li, and Xiong-Fei Jiang. New approaches in agent-based modeling of complex financial systems. *Frontiers of Physics*, 12(6):128905, April 2017.

[12] Peter Crosbie and Jeff Bohn. Modeling default risk: Modeling methodology. *KMV corporation*, 2003.

[13] Bradley Efron and Gail Gong. A Leisurely Look at the Bootstrap, the Jackknife, and Cross-Validation. *The American Statistician*, 37(1):36–48, 1983. Publisher: [American Statistical Association, Taylor & Francis, Ltd.].

[14] Dmitry Ivanov, Alexandre Dolgui, and Boris Sokolov. Ripple Effect in the Supply Chain: Definitions, Frameworks and Future Research Perspectives. In *International Series in Operations Research and Management Science*, pages 1–33. January 2019. Journal Abbreviation: International Series in Operations Research and Management Science.

[15] Nick W Kraemer and Jon Palmer. 2021 Annual Global Corporate Default And Rating Transition Study. 2021.

[16] Anna Ledwoch, Hakan Yasarcan, and Alexandra Brintrup. The moderating impact of supply network topology on the effectiveness of risk management. *International Journal of Production Economics*, 197:13–26, March 2018.

[17] Haobin Li, Giulia Pedrielli, Loo Hay Lee, and Ek Peng Chew. Enhancement of supply chain resilience through inter-echelon information sharing. *Flexible Services and Manufacturing Journal*, 29(2):260–285, June 2017.

[18] Yuhong Li and Christopher W. Zobel. Exploring supply chain network resilience in the presence of the ripple effect. *International Journal of Production Economics*, 228:107693, October 2020.

[19] Robert C. Merton. Theory of Rational Option Pricing. *The Bell Journal of Economics and Management Science*, 4(1):141–183, 1973. Publisher: [Wiley, RAND Corporation].

[20] C. Otto, S. N. Willner, L. Wenz, K. Frieler, and A. Levermann. Modeling loss-propagation in the global supply network: The dynamic agent-based model acclimate. *Journal of Economic Dynamics and Control*, 83:232–269, October 2017.

[21] Constantin Pavel. Introduction to Merton Jump Diffusion Model.

[22] Hannah Ritchie, Pablo Rosado, and Max Roser. Natural Disasters. *Our World in Data*, December 2022.

[23] Wim Schoutens and Jessica Cariboni. *Levy Processes in Credit Risk*. John Wiley & Sons, June 2010. Google-Books-ID: DjmvZ5CSmxAC.

[24] Mamadou Seck, Ghaith Rabadi, and Christian Koestler. A Simulation-based Approach to Risk Assessment and Mitigation in Supply Chain Networks. *Procedia Computer Science*, 61:98–104, January 2015.

[25] Kathryn E. Stecke and Sanjay Kumar. Sources of Supply Chain Disruptions, Factors That Breed Vulnerability, and Mitigating Strategies. *Journal of Marketing Channels*, 16(3):193–226, June 2009. Publisher: Routledge _eprint: https://doi.org/10.1080/10466690902932551.

[26] Mitja Steinbacher, Matthias Raddant, Fariba Karimi, Eva Camacho Cuena, Simone Alfarano, Giulia Iori, and Thomas Lux. Advances in the agent-based modeling of economic and social behavior. *SN Business & Economics*, 1(7):99–99, 2021. Place: Cham Publisher: Springer International Publishing.

[27] Hossein Tabari and Patrick Willems. Trivariate Analysis of Changes in Drought Characteristics in the CMIP6 Multimodel Ensemble at Global Warming Levels of 1.5°, 2°, and 3°C. *Journal of Climate*, 35(18):5823–5837, September 2022. Publisher: American Meteorological Society Section: Journal of Climate.

[28] HTP Thao and Quan-Hoang Vuong. A Merton Model of Credit Risk with Jumps. 2:97–103, May 2015.