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Mitigating disruptions: Assessing the role of regulatory measures in fuel supply chain resilience during floods in Brazil

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Climate change has emerged as one of the most pressing global challenges, with extreme weather events increasingly disrupting supply chains worldwide. In April 2024, catastrophic floods in Rio Grande do Sul, Brazil, severely affected the fuel distribution infrastructure, prompting regulatory intervention through temporary relief measures. This paper presents a spatial competition model to assess the resilience of the fuel supply chain and to evaluate some of the regulatory responses. We develop a three-echelon supply chain model that incorporates diesel and biodiesel suppliers, distributors, and retailers, and simulate market dynamics through iterative price updates while considering transportation costs, capacity constraints, and mandatory biofuel blend requirements. Our analysis reveals that supply overcapacity significantly influences price stability, with tighter capacity leading to higher prices. When simulating the removal of a major biodiesel supplier - mirroring occurred real events - our results suggest that reducing mandatory biodiesel content may have had unintended consequences, potentially increasing overall fuel costs to retailers. These findings demonstrate the complex interplay between regulatory interventions and market dynamics during supply chain disruptions, offering insights for policymakers and industry stakeholders in developing more effective resilience strategies.

Keywords: Supply Chain, Resilience, Fuel, Biodiesel, Extreme Weather Event, Regulatory measures

1. Introduction

The impact of climate change is becoming increasingly evident and severe causing supply chain disruption (Ali et al., 2023). Consequently, supply chain resilience — the capacity to prepare for, withstand, and quickly recover from extreme events — has become a significant topic of discussion among practitioners, policymakers, and researchers (Hosseini et al., 2019).

In April-May 2024, hundreds of towns were flooded in the Brazilian state of Rio Grande do Sul, with casualties and thousands of citizens displaced from their homes (Buschschlüter, 2024). Among the consequences, many of the fuel production and distribution facilities were underwater, which impacted the fuel supply of the state, increasing the challenges to post-disruption recovery. With the objective of making fuel distribution operations more flexible, the National Agency for Petroleum, Natural Gas, and Biofuels (ANP) approved some temporary relief measures, among which was temporary relaxation of the blend of biodiesel with diesel oil and ethanol with gasoline (ANP, 2024).

Brazil has a mandatory biodiesel blend policy, which requires distributors blending a specific percentage of biodiesel with regular diesel A (i.e., pure fossil diesel without any biodiesel content) to produce diesel B, which is then sold to retailers and larger consumers. This policy is overseen by the National Energy Policy Council (CNPE) and regulated and enforced by ANP. The mandatory blend level is set to increase from 14% to 15% in 2025 (IEA, 2023). During the Rio Grande do Sul floods, the obligation was relaxed to as low as no biodiesel (depending on the content of diesel sulfur) in the entire state, with a progressive recovery to the prescribed levels.

Our goal in this article is to develop a supply chain spatial competition model to assess the impacts of the regulatory relaxation measure. The standard model of spatial competition, introduced by Hotelling (1929), considers firms competing in both prices and locations along a linear market, and the spatial allocation can also be interpreted as a "consumers' preference space" to justify goods' differentiation. Its ideas are still used to these days to study different markets such as health care (Kuchinke and Zerth, 2015), retail (Chai et al., 2021) and fuels (Luo and Moschini, 2019).

In Hotteling's foundational framework, consumers are modeled as uniformly distributed along a market space, choosing firms based on the lowest total cost (price plus transportation). While this continuous distribution aids theoretical insights, real markets often show discrete demand patterns. For example, in fuel retail markets, demand nodes like gas stations are discretely located with specific demand (Netz and Taylor, 2002). This discreteness affects competitive dynamics and market outcomes, which continuous-space models may not capture.

In spatial competition models under Hotelling's framework, firms typically make pricing decisions simultaneously and without cooperation. This simultaneity implies that when setting prices, each firm must act without knowledge of its competitors' choices, instead forming expectations about their behavior. When firms can accurately anticipate their competitors' actions, the market tends toward a Nash Equilibrium (Tirole, 1988). A Nash equilibrium of prices occurs when each firm sets its price at a level where it has no incentive to change, given the prices set by its competitors. In this equilibrium no firm can increase its profits by unilaterally changing its price and each firm's price is the best response to the prices set by other firms (Osborne and Rubinstein, 1994).

2. Methodology

We propose an agent-based three-echelon supply chain model comprising diesel A (A) and biodiesel (B) suppliers, distributors who mix these products in the right compulsory amount, and retailers. The network structure is defined by nodes (with capacity and demand) connected by edges representing distance-based travel costs. Through agent-based iterative simulation, we evaluate how price competition affects cost structures and, ultimately, market supply capability.

2.1. *Network structure*

We choose an arbitrary number of agents for each echelon, which increases as we go downstream through the supply chains, reproducing the Brazilian market: 3 diesel A suppliers (A), 5 biodiesel suppliers (B), 10 distributors (D), and 50 retailers (R). The demand of each retailer is first established as a random integer number between 1 and 10. Each individual distributor demand of A and B products is a result of the attribution of retailers to it, multiplied by the fraction of each component in the mixture. As the biodiesel proportion is most commonly referred to, that is defined as $x = 14\%$ for B and $(1-x) = 86\%$ for A when not explicitly indicated otherwise.

An overcapacity factor, α, is included to account for the proportion of the summed supply capacity, of all agents in a group, that exceeds the total demand of the retailers. Using c_i for the capacity of an individual firm and d_j as the individual demand of a retailer, that can be expressed as in Eq. (1):

$$\sum_i c_i = \alpha \sum_j d_j \ \forall\, i \in \{A, B, D\}, j \in R \quad (1)$$

The capacity varies between agents, as is usually the case in real markets. The capacity proportion decreases as the index of a firm in their group increases, so D0 has the higher capacity between distributors (and D9 has the lowest). For the A firms, with 3 agents, they have the following proportion: 3:2:1. For B firms, with 5 agents, the proportion of capacity between them is 5:4:3:2:1, and so on. Considering that a given echelon e has n_e firms, the individual capacity of each firm c_i in that echelon is given by Eq. (2):

$$c_i = \frac{n_e - i}{1 + 2 + ... + n_e} \times \sum_{j=0}^{n_e - 1} c_k \qquad (2)$$
$$\forall\, i \in \{0, 1, ..., n_e - 1\},\ e \in \{A, B, D\}$$

The firms are randomly placed in a 1x1 square space using *x* and *y* coordinates are drawn from a uniform distribution in $[0, 1)$. Then, the euclidean distance from each supplier to all the other firms in the downstream echelon is calculated to compose the distance matrix. The travel cost is set as a constant value of \$2 per unit of distance and unit of the fuel transported.

2.2. *Agent behavior*

Retailers are assumed to be rational economic agents who minimize their total cost (price plus travel cost) when purchasing fuel, subject to distributor's capacity constraint and their own reservation price.

We decided to introduce capacity constraints for the suppliers and distributors as, in disruption episodes, the temporary lack of firms' capacity may be one of the factors that impact prices and, ultimately, causes a shortage of fuels for the final consumer. This constraint means that, even though some consumers are willing to pay the price a firm is charging, the firm cannot meet all of its demand since it cannot sell more than it is capable of producing. In our model, we process the buyers sequentially one after the other, evaluating their options. That is a kind of "first come, first served" rule, where the buyer with the smaller index has precedence over the others. This might be not so realistic since in real life situations, firms would apply some rule to decide which consumers to serve (e.g. prioritizing contracts, consumers with stronger relationship, or any other).

Buyers also have a reservation price, which is the highest amount they are willing to pay. That means that, when a retailer evaluates distributors, if no available seller offers a price, including transportation costs, below the reservation price, the retailer will not make a purchase. We considered that all the retailers have the same arbitrary reservation price of \$10 per unit of fuel.

Distributors are both sellers and buyers. Acting as a seller, given a set of prices from all other distributors, a distributor calculates its best response price by maximizing its profit, subject to capacity constraints. Given their discontinuous and non-concave profit function (Fig. 3), this is done by iterating through a range of possible prices (\$0.01 increments up to retailer reservation price) and calculating the resulting profit for each price.

The profit is calculated as the sum of the demands of all retailers that would choose that distributor under that set of prices, multiplied by the difference between the distributor's price and the cost of the mixture of A and B products it buys from its suppliers. Given a set of $p_1, ..., p_n$ prices of the n sellers, the i-th firm faces a demand $D_i(p_1, ..., p_n)$ while the costs are $c_i = (1 - x)c_{iA} + xc_{iB}$. Therefore, the profit Π_i is

$$\Pi_i(p_1, ..., p_n) = (p_i - c_i) \cdot D_i(p_1, ..., p_n) \quad (3)$$

Acting as buyers, the rules applied to distributors are similar to those applied to retailers. The distributor also has a reservation price, in which they will not pay more for each input component (c_{iA} and c_{iB}) than the price they can sell the mix to retailers (p_i). Therefore,

$$c_{iA} \leq p_i \quad \text{and} \quad c_{iB} \leq p_i \qquad (4)$$

while the i^{th} distributor's demands for each mixture component, D_{iA} and D_{iB}, are given by

$$D_{iA} = (1 - x)D_i \quad \text{and} \quad D_{iB} = xD_i \qquad (5)$$

Suppliers are similar to distributors. Each supplier (A or B) calculates its best response price by maximizing its profit, subject to capacity constraints. For simplicity, we assume no cost is associated to the suppliers and therefore their profit is calculated as the sum of the demands of all distributors assigned to the supplier, multiplied by the supplier's price.

Each distributor is assigned to the supplier that offers the lowest price, including travel costs, subject to the supplier's capacity constraint, in the same way as retailers are assigned to distributors.

2.3. *Iterative price update*

Because of the discontinuous nature of the best response price curves, it is unlikely to reach a

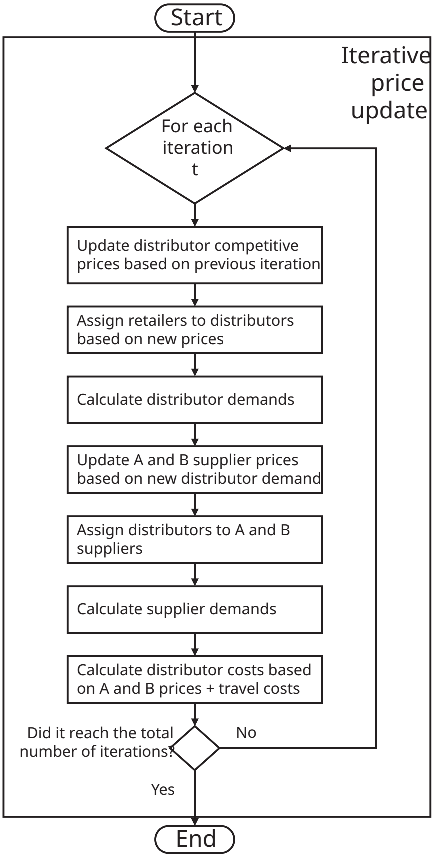

Fig. 1. Flowchart of the iterative price update algorithm

Nash equilibrium in prices. This occurs especially because a finite number of fully informed buyers immediately respond to minimal price increases by changing their chosen supplier.

Although Nash equilibrium is not possible, we propose a different set of rules to evaluate the direction that competitive prices take from a given initial price in a three-echelon supply chain, explicitly considering the costs incurred by distributors in procuring products. The aim is to capture the dynamic interactions among agents and their responses to changing market conditions. The steps involved in each iteration (Fig. 1) are:

(i) Distributor Price Adjustment: At each iteration t, each distributor i picks the price $p_{i_t}^*$ that maximizes its profit, considering the actual level of prices of all the other distributors $(p_1, ..., p_{i-1}, p_{i+1}, ..., p_n)_{t-1}$. The initial prices $(p_1, ..., p_n)_{t=0}$ were arbitrarily set as \$5 per unit of fuel for all distributors.

(ii) Retailer Assignment: Retailers are assigned to distributors based on updated set of prices $(p_1, ..., p_n)_t$. and their individual demands.

(iii) Distributors‘ Demand Calculation: The demand is calculated aggregating the demand from all retailers assigned to each distributor.

(iv) Supplier Price Adjustment: A and B suppliers adjust their prices for iteration t based on the demand from distributors and their competitor’s available prices from iteration $t-1$.

(v) Distributor-Supplier Assignment: Distributors are assigned to suppliers based on updated prices and their individual demands.

(vi) Suppliers‘ Demand Calculation: The demand for each supplier is calculated from distributors’ assignments. It aggregates the demand from all distributors assigned to each supplier. The suppliers prices in $t = 0$ were set as \$2.5 per unit of A component and \$3 per unit of B component.

(vii) Distributors‘ Costs calculation: Once each distributor is assigned to A and B suppliers, we can update the distributor costs based on A and B prices summed to travel costs.

200 iterations are used to see the convergence of the model around a certain level of prices, even though the complete Nash equilibrium would not be reached as explained.

2.4. *Simulated scenarios*

Resource limits, i.e., constraints on output based on availability of the factors of production, such as Supplier, Production and Distribution capacity, are known to be vulnerability factors that improve risks in supply chains. On the other hand, *Capacity*, defined as availability of assets to enable sustained production levels, such as reserve capacity and redundancy are capability factors that mitigate those risks, driving to balanced Resilience and improved performance (Pettit et al., 2010).

We evaluate how the level of overcapacity, represented by α, changes the price dynamics and the

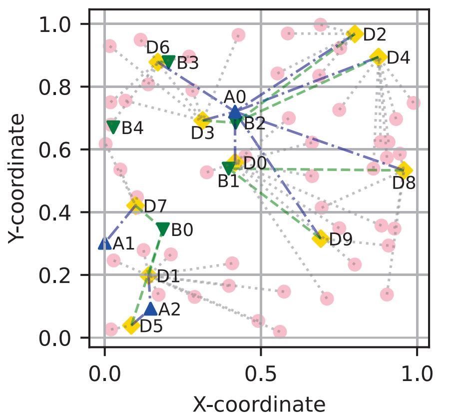

Fig. 2. Spatial positioning of agents. Lines represent the assignment of retailers to distributors and of these to A and B suppliers. ▲: A suppliers, ▼: B suppliers, ◆ : Distributors, ●: Retailers.

supply chain total costs. The values of α tested are 10%, 40%, 80% and 100%.

Simulating a disruptive scenario, similar to what happened during the floods in Rio Grande do Sul, a biodiesel producer is removed (i.e. its capacity is brought to zero). Using an overcapacity factor $\alpha = 80\%$, the biggest biodiesel supplier is taken away, which reduces the total biodiesel supply capacity in one third or, in other terms, reducing this component's supply capacity from 180% to 120% of the equivalent retailers' demand.

Inspired by the regulatory relief measures took by ANP, we also simulated other two scenarios where, while removing the biggest biodiesel supplier, the mixtures proportions where reduced to 7% and to 0% of biodiesel in the mixture.

3. Results and Discussion

3.1. *Assignment of buyers to sellers*

The spatial competition model can be easily visualised as a map where the agents and their buyer-seller relationships can be plotted as shown in Figure 2.

The nodes in Fig. 2 represent the spatial distribution of the 3-echelon supply chain agents: Suppliers, distributors and retailers. The lines connecting these nodes represent the commercial relationship that would be established under the current set of prices and capacities.

The figure shows clusters of influence zones for each distributor, with some deviations from expected equidistant boundaries due to capacity constraints. For example, despite being closer to D8, several retailers in the middle-right area are supplied by D4, as D8's capacity (6.4% of total demand) is quickly exhausted by retailers that made earlier choices.

3.2. *Reacting to competitors prices*

Competitive prices are achieved when every agent seeks to maximize its profit. As shown in Fig. 3, starting from a price equal to zero, if all other firms keep their prices constant, a firm can increase its own price to see its profit grow. This can continue until one or many of its potential clients would swap to another supplier producing a profit reduction. If the price increase continues, more clients abandon this supplier, and, above a certain price, there will be no client, and the profits go down to zero. If costs were included, prices below unitary costs would deliver negative profits (i.e., losses) and the curve would simply be translated downward on the ordinate axis.

Firm D2 has a higher capacity than firm D4. That partially explains why, in Fig. 3, for almost all the considered prices, the total profits earned

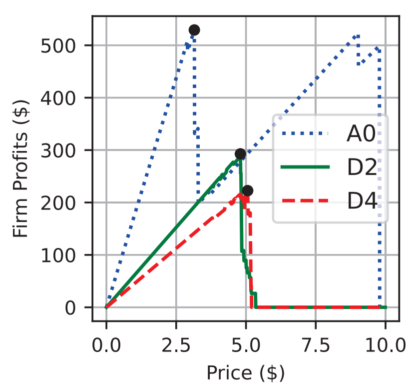

Fig. 3. Profit for firms A0, D2 and D4 as a function of the price charged, keeping all the other firms prices fixed at $2.5 and $5.0 for A and B suppliers, respectively. All the firms' costs are disregarded. The black dots represents the maximum possible profit.

by D2 are higher than those earned by D4. Besides the general aspect of both D2 and D4 profit curves looking similar, the maximum profit is positioned of different prices. That means that, if all other distributors where to charge a price of $\$5$, firm D2 best response would be a price less than $\$5$, while D4's best price in that situation would be slightly higher than its competitors.

Firm A0's profit curve, shown in Fig. 3, displays two peak regions. Initially, as prices rise from zero, profits peak on the left-hand part of the plot as consumers pay more. Further price increases cause some buyers to leave, but not all. When prices exceed $\$8$, another peak occurs on the graph's right-hand side. That clients stay with this firm at prices as high as that only because all the other firms reached their capacity limit and the consumers do not have another alternative. Going further, the buyers reach their reservation price (in this example, $\$10$) one after the other, the farther ones before the closer ones, and profits decline to zero. This dynamic is used to update each firm's price, as explained in section 2.3.

3.3. *Competition model*

After 200 iterations, prices move away from initial values and tend to be included in some bounds as seen in Fig. 4. In the last 50 iterations, the A prices ranged from $\$0.10$ to $\$1.24$, while B prices varied from $\$0.22$ to $\$1.79$ and the final mixture from $\$0.89$ to $\$2.84$, among all agents.

With the resulting prices after each iteration, it is possible to calculate the mean price of components A and B, as well as the mean transportation cost payed by each distributor to move them from the supplier to its site. It is also possible to calculate the mean price charged by the distributors, but it is convenient to express the distributor margin, which is the difference between the distributor's price and the costs incurred to buy the components. On top of that, there is the mean transportation cost paid by the retailers. For the base scenario, this is presented in Fig. 5-c.

3.4. *Influence of overcapacity*

The influence of the spare capacity level over the prices after several iterations was evaluated, for four different values of the overcapacity factor α (see Fig. 5). For all plots in Fig. 5 the individual costs are stacked: Costs of acquisition by the distributors, which includes the price and the transportation costs for products A and B, distribution margins and final transport cost to retailer. In all cases, the costs associated with B product are smaller, compared to product A and distribution costs, because product B is present in only a minor portion of the total mixture (14%).

When the supply capacity is too tight, closer to the demand, prices tend to reach the reservation prices, as shown in Fig. 5-a for $\alpha = 10\%$, with A prices representing the higher proportion of total costs. In this scenario, firm A0 has the potential to exercise its market power, reaching higher profits by charging prices slightly higher than its competitors, while the competitors hit their maximum supply capacity.

Going to higher overcapacity amounts, average prices tend to be more stable and smaller values, as observed in Fig. 5 c and d. These findings strengthen the intuition that capacity restrictions (for example, during a disruption) could lead to an increase in price levels.

3.5. *Impact of supplier removal*

In order to replicate a scenario that occurred during the Rio Grande do Sul floods, when the most central biodiesel producer‘s facilities were completely flooded, we removed the largest biodiesel supplier from the simulation, keeping all other capacities constant. The total cost incurred by retailers, which includes the mean price charged by the distributors and the mean transportation costs (both weighted by the volume negotiated), is presented in Fig. 6. In this figure, other scenarios were included, inspired by the measures taken by the regulatory body ANP. Beyond the regular scenario of 14% of biodiesel in the mixture, two additional scenarios are presented: mixture of 7% and completely removing the biodiesel from the mixture. For all scenarios shown in Fig. 6, the costs stay between $2 and $3 for all scenarios. Visual inspection of the graph suggests that price levels are lower prior to the removal of firm B0. Furthermore, after the removal of firm B0, scenar-

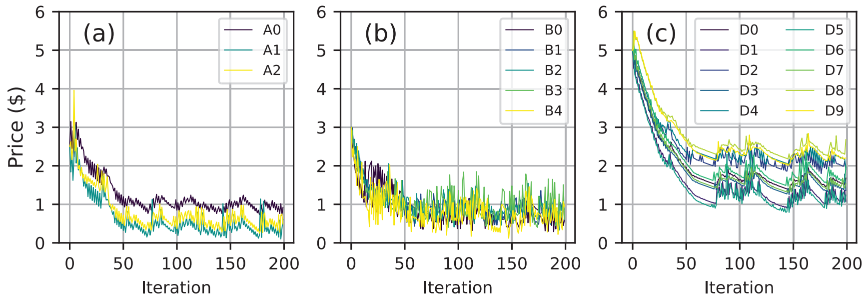

Fig. 4. Evolution of prices over 200 iterations for (a) A suppliers, (b) B suppliers and (c) Distributors.

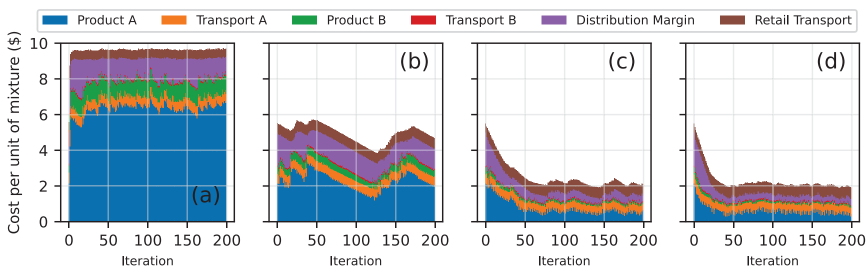

Fig. 5. Evolution of mean individual costs per unit of mixture, varying the overcapacity factor α. (a) $\alpha = 10\%$, (b) 40%, (c) 80% and (d) 100%.

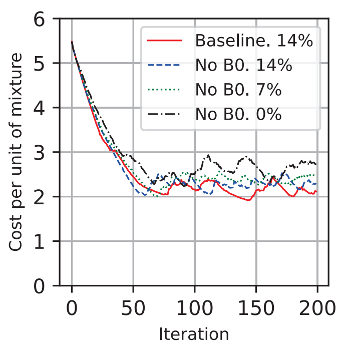

Fig. 6. Total Retailers costs, comparing three scenarios of mixture proportion when the larger biodiesel supplier is removed with the base scenario.

ios with higher biodiesel content result in reduced price levels.

For each scenario, the values of the first 75 iterations were discharged, and the mean and standard deviation of the last 125 iterations where calculated (see Table 1).

Table 1. Total retailers' costs after removing the first 75 iterations, under 4 different scenarios.

Scenario Firm removed	x	Retail costs Mean	Std. Dev.
No removal.	14%	2.17	0.13
B0	14%	2.29	0.09
B0	7%	2.40	0.08
B0	0%	2.61	0.17

The removal of B0 resulted in higher mean costs observed by retailers in the simulated scenarios. That also means that, if B0 is removed, decreasing the percentage of component B in the mixture is associated with higher costs to retailers. Since the reduction of component B in the mixture means an increase in component A, this is accompanied by a reduction in the idle capacity of the suppliers of A. As noted earlier, the reduction of overcapacity might lead to price increases in our model, specially in A product with less competitors, which can explain the increase in total costs.

That results suggest that the regulatory body's relief measures might have had an unintended impact in raising the total cost of fuel to retailers. However, more research is necessary to conclude that, including previously validating the model using real data, which is a path for new research.

4. Conclusion

This paper presents an agent-based spatial competition model inspired by the Brazil's fuel supply chain. The model can used to evaluate supply-chain resilience with particular focus on the impact of regulatory measures during extreme weather events. Our analysis demonstrates that market overcapacity significantly influences price stability and supply chain resilience. When supply capacity is tight (10% overcapacity), prices tend to rise toward reservation levels, while higher overcapacity levels (80-100%) lead to more stable and lower average prices.

Our simulation of the Rio Grande do Sul floods scenario, where we removed the largest biodiesel supplier, revealed possible unexpected consequences of regulatory interventions. In contrast to intuition, reducing the requirement for a mandatory biodiesel mixture, a measure intended to alleviate supply chain stress, led to higher total costs for model retailers. While these results provide valuable insights for policy makers and industry stakeholders, future research should include other regulatory interventions, validate current findings against empirical data and explore additional regulatory mechanisms for enhancing supply chain resilience.

To ensure reproducibility all the complete code, data, and environment setup conducted using Python within a Google Colab notebook are accessible at:

`https://gist.github.com/JardelDuque/49705c20d17a99a689714806b8a1b450`.

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