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Modeling Market Adaptation and Regulatory Flexibility for Fuel Supply Resilience

Jardel Farias Duque

Civil and Environmental Engineering Department, University of Strathclyde, United Kingdom/National Agency for Petroleum, Natural Gas and Biofuels (ANP), Brazil. E-mail: jardel.farias-duque@strath.ac.uk

Raphael Moura

National Agency for Petroleum, Natural Gas and Biofuels (ANP), Brazil.

Edoardo Patelli

Civil and Environmental Engineering, University of Strathclyde, UK. E-mail: edoardo.patelli@strath.ac.uk

Fuel supply chains are critical infrastructures exposed to disruptions, price volatility, and regulatory constraints. While computational models are increasingly used to assess supply chain resilience, most assume fully rational agents. This paper relaxes that assumption by incorporating loss aversion — a core feature of bounded rationality — into a three-echelon spatial competition model of a fuel supply chain. Buyers evaluate supplier choices through a reference-dependent utility function in which losses weigh more heavily than equivalent gains, parameterized by a loss aversion coefficient λ. Using agent-based simulation across multiple λ values, we analyze how behavioral preferences affect equilibrium prices, convergence dynamics, and system response to price shocks. Results show that higher loss aversion increases equilibrium landed costs and accelerates convergence under baseline conditions. However, under large perturbations, loss-averse markets exhibit persistent oscillations not observed in the loss-neutral benchmark. The study contributes a methodological extension to supply chain resilience modeling by demonstrating that bounded rationality is not a marginal refinement but a structural determinant of system behavior. Incorporating behavioral realism is therefore an option for developing more credible stress-testing tools and decision-support frameworks for critical supply chains.

Keywords: Bounded rationality, loss aversion, supply chain resilience, behavioral economics, fuel markets, agent-based modeling.

1. Introduction

Fuel supply chains are critical infrastructures whose reliable functioning underpins economic stability, mobility, and public welfare. Ensuring continuous fuel availability involves coordinating complex, multi-echelon networks that connect refineries and biofuel plants to thousands of customers through distributors and retailers. These networks operate under tight capacity constraints, spatial frictions, regulatory blending mandates, and volatile global commodity markets. As recent global disruptions have demonstrated, supply chains exposed to climatic, geopolitical, and operational shocks are increasingly vulnerable to systemic instability (Ivanov, 2021; Akkermans and Van Wassenhove, 2018; OECD, 2025).

Supply chain resilience (SCR) has therefore become a central topic in operations research and risk analysis. SCR is commonly defined as the ability of a system to withstand, adapt to, and recover from disruptions while maintaining acceptable performance levels (Christopher and Peck, 2004; Sheffi and Rice Jr., 2005; Hosseini et al., 2019). Quantitative modeling plays a crucial role in operationalizing this concept, enabling stress-testing, scenario analysis, and the evaluation of mitigation strategies in controlled environments (Ivanov and Dolgui, 2021). However, most analytical and computational models of supply chains rely on the assumption of fully rational agents who optimize decisions with perfect information and stable preferences.

This assumption is analytically convenient but behaviorally restrictive. A large body of evidence from behavioral economics demonstrates that economic agents systematically deviate from the rational-actor paradigm (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). One of the most robust and empirically validated findings is loss aversion: the tendency for losses to become more relevant than equivalent gains. In market settings, loss aversion alters price perception, switching behavior, and competitive dynamics (Heidhues and Kőszegi, 2008; Karle and Peitz, 2014; DellaVigna, 2009). Yet, despite its established relevance in industrial organization and behavioral economics, loss aversion remains largely absent from supply chain resilience modeling.

During disruptions, agents face abrupt price changes, capacity reallocation, and supplier switching decisions — precisely the contexts in which reference dependence becomes salient. Ignoring such behavioral mechanisms may bias predictions of market adjustment and recovery trajectories. Emerging work in behavioral operations management suggests that bounded rationality, fairness concerns, and reference effects can materially alter operational outcomes (Bendoly et al., 2006; Goudarzi et al., 2023). Nevertheless, these insights have only marginally penetrated quantitative resilience modeling, particularly in multi-echelon, spatially explicit supply networks.

In previous work (Duque et al., 2025), a three-echelon spatial competition model of the diesel–biodiesel supply chain was developed to examine how regulatory flexibility affects market outcomes under disruption. That framework assumed loss-neutral agents and focused on structural and policy variables. The present study advances that line of research by introducing a behavioral layer into the model: buyers evaluate supplier choices through a reference-dependent utility function that incorporates loss aversion.

The central research question is: How does loss aversion affect equilibrium outcomes, convergence dynamics, and shock-response behavior in a spatially structured fuel supply chain model? To address this question, we embed prospect-theoretic preferences into an agent-based spatial competition framework in which sellers iteratively update prices under capacity constraints and buyers select suppliers based on utility changes relative to their most recent transaction. Agent-based modeling is particularly suited for capturing heterogeneous adaptation and emergent dynamics in supply networks (Macal and North, 2010; Nair and Vidal, 2011).

Our findings indicate that behavioral parameters are not merely micro-level refinements but structural determinants of aggregate system performance. Loss aversion increases equilibrium landed costs, accelerates convergence under baseline conditions, and generates qualitatively distinct recovery patterns following large perturbations. The effects are not uniformly stabilizing: while moderate shocks may be dampened by behavioral "stickiness", extreme shocks can induce persistent oscillations. These results suggest that resilience assessments based solely on rational-agent assumptions may overlook endogenous stabilizing — or destabilizing — forces embedded in bounded rationality. Incorporating behavioral realism is therefore an interesting step toward more credible stress-testing tools and future Digital Twin applications for decision support.

2. Methodology

2.1. *Supply chain model overview*

We employ a three-echelon spatial competition model inspired by Brazil's diesel-biodiesel supply chain, but that could be adapted to any other similar supply chain involving raw-to-product conversion. In our case, the echelons comprise the components suppliers - diesel-A (fossil diesel) and biodiesel suppliers -, distributors who blend the products, and retailers. Agents are placed via random spatial coordinates in a unit square, with distances determining travel costs.

The network configuration contains: 3 diesel-A suppliers (A), 5 biodiesel suppliers (B), 10 distributors (D), and 50 retailers (R). Retailers have fixed demands, randomly drawn from the uniform distribution $[1, 10]$ units. An overcapacity factor $\alpha = 1.4$ ensures total supply capacity exceeds total demand in 40%:

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

where c_i is individual firm capacity and d_j is individual buyer demand. Capacity is heteroge-

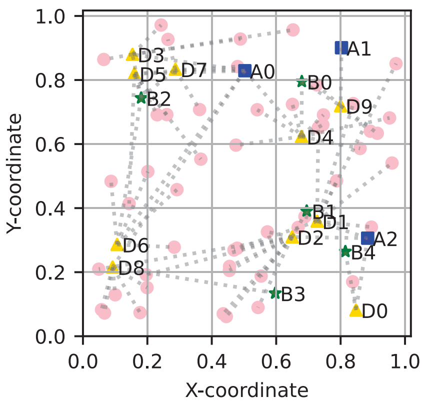

Fig. 1. Spatial positioning of agents. Lines represent the assignment of retailers to distributors and of these to A and B suppliers. ■: A suppliers, ⋆: B suppliers, ▲ : Distributors, ●: Retailers.

neous, decreasing across firm indices within each echelon (largest firms indexed as 0), following the proportions $n_e : (n_e - 1) : \ldots : 1$ for an echelon with n_e firms.

The spatial competition model can be easily visualized as a map where the agents and their buyer-seller relationships can be plotted as shown in Figure 1.

The nodes in Fig. 1 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.

2.2. *Loss aversion implementation*

The main innovation is incorporating loss aversion into buyers' decisions. Following prospect theory (Kahneman and Tversky, 1979), agents evaluate outcomes relative to a reference point. Let Δp denote the change in price per unit relative to a previous transaction, and Δt the change in per-unit transportation cost. An agent's utility for gains ($\Delta \geq 0$) and losses ($\Delta < 0$) is:

$$u(\Delta) = \begin{cases} \Delta & \text{if } \Delta \geq 0 \text{ (gains)} \\ -\lambda|\Delta| & \text{if } \Delta < 0 \text{ (losses)} \end{cases} \quad (2)$$

The parameter $\lambda \geq 1$ represents loss aversion intensity. When $\lambda = 1$, agents are loss-neutral (classical rational actor). As λ increases, losses weigh more heavily: a loss of magnitude $|\Delta|$ generates dis-utility $\lambda|\Delta|$, exceeding the utility of a gain of magnitude $|\Delta|$.

Each agent evaluates suppliers/prices by combining price and transportation cost changes relative to their reference point - in our case, their most recent transaction. Agents with high loss aversion require larger price reductions to justify switching to a new supplier located at a greater distance, as the loss of relationship stability and perceived risk outweighs marginal cost savings.

2.3. *Experimental design*

2.3.1. *Baseline equilibrium analysis*

We simulate four market configurations corresponding to $\lambda \in \{1.0, 1.5, 2.0, 2.25\}$. The value $\lambda = 1.0$ represents the rational-actor baseline (no loss aversion). Values $\lambda = 1.5, 2.0, 2.25$ reflect increasing degrees of boundedly-rational behavior; $\lambda = 2.25$ is consistent with empirical estimates from prospect theory studies (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), with lower values being reported in other empirical setups (Gächter et al., 2022).

For each λ value, we conduct 150 iterations of simultaneous price updates by each seller to maximize profit given competitors' prices, subject to capacity constraints. Buyers are then assigned to sellers via a greedy algorithm: each buyer (in order) selects the seller offering the highest variation in total utility ($u(\Delta p) + u(\Delta t)$), subject to seller capacity and the buyer's reservation price.

We record mean landed cost per unit (i.e., price + unit transportation cost), market prices, and allocation decisions at each iteration. We also calculate the convergence iteration (first iteration where rolling coefficient of variation over 20-iteration windows falls below 5% for all products).

2.3.2. *Perturbation-stability analysis*

After each market reaches equilibrium under baseline conditions, we apply symmetric price shocks of $+100\%, +50\%, +10\%, -50\%$ to all sellers. Each perturbation triggers 150 new iterations of

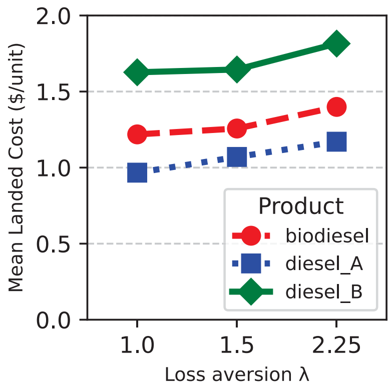

Fig. 2. Mean landed cost per unit vs. loss aversion factor λ for each product, considering 20 iterations after convergence

price/quantity responses. We measure recovery as the number of iterations required for mean landed costs to return within $\pm 5\%$ of the rolling-window mean, how quick the model responds to price shocks.

3. Results

3.1. *Effect of loss aversion on equilibrium*

Loss aversion produces a clear pattern: $\mathbf{h}igher\ \lambda$ increases equilibrium landed costs. As shown in Fig. 2, for diesel-B (the final product), mean landed cost increases from \$1.63 at $\lambda = 1.0$ to \$1.82 at $\lambda = 2.25$, a 11.6% increase.

Component products show similar patterns: diesel-A landed costs increase from \$0.97 ($\lambda = 1.0$) to \$1.17 ($\lambda = 2.25$), and biodiesel from \$1.22 to \$1.40.

This result is consistent with previous works in the Economics and industrial organization literature that state that loss aversion generally raises equilibrium prices in imperfectly competitive markets. In Heidhues and Kőszegi (2008)'s model, consumers react much more strongly to unexpected price increases than to unexpected price decreases. Because a price cut attracts relatively few additional buyers—while a price increase triggers a disproportionately large perceived loss—firms face fewer incentives to undercut rivals, which softens competition and supports higher markups. Karle and Peitz (2014) likewise demonstrate that loss-averse consumers are less price sensitive in equilibrium, allowing firms to sustain higher prices.

3.2. *Convergence behavior*

Convergence trajectories of the mean landed costs for all products, under all λ values tested, are presented in Fig. 3. Vertical dashed lines mark the iteration when the trajectory of the mean landed cost reaches stability, keeping the rolling coefficient of variation for 20 iterations window under the 5% threshold.

Starting from the same arbitrary initial prices, we can notice that the landed costs decrease in a non-smooth way, reaching convergence for almost all products, except for diesel A and biodiesel under $\lambda = 2.0$.

The most important finding when comparing the graphs is that *loss aversion accelerates equilibration*. The curves for $\lambda = 1.5$ and $\lambda = 2.25$ reach stable plateaus at 45–65 iterations, whereas $\lambda = 1.0$ requires almost 130 iterations to reach convergence for all products. This acceleration occurs because sellers must offer sharper price reductions to offset higher transportation costs and to attract loss-averse buyers located farther away.

On the other hand, once a price is perceived as "fair", buyers resist deviation, stabilizing the market. In other words, loss-averse agents quickly anchor to a stable price level. This behavioral anchoring reduces persistent price oscillations characteristic of a rational-agent model.

3.3. *Perturbation-stability analysis*

Figure 4 displays the temporal evolution of mean landed costs before and after simultaneous price shocks applied to all sellers across all markets. The vertical dashed line marks the perturbation point, separating the baseline equilibrium phase (left) from the post-shock adjustment phase (right).

The behavior of the simulated markets in Fig. 4 differs depending on the sign of the price shock. Following negative price shocks (the 50% decrease in panels d/h), mean landed costs do not return to pre-shock levels but instead stabilize at

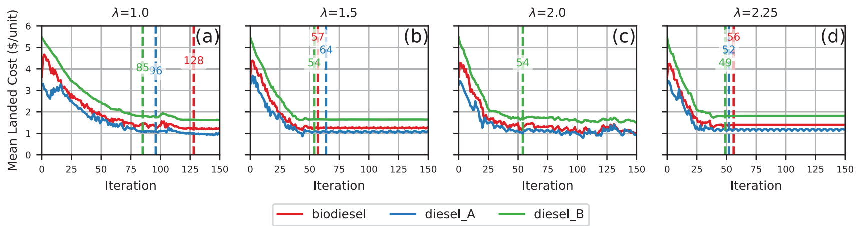

Fig. 3. Evolution of mean landed costs over 150 iterations for different values of loss-aversion factor λ: (a) 1.0, (b) 1.5, (c) 2.0 and (d) 2.25. Dashed lines represent the convergence iteration for each product, when reached.

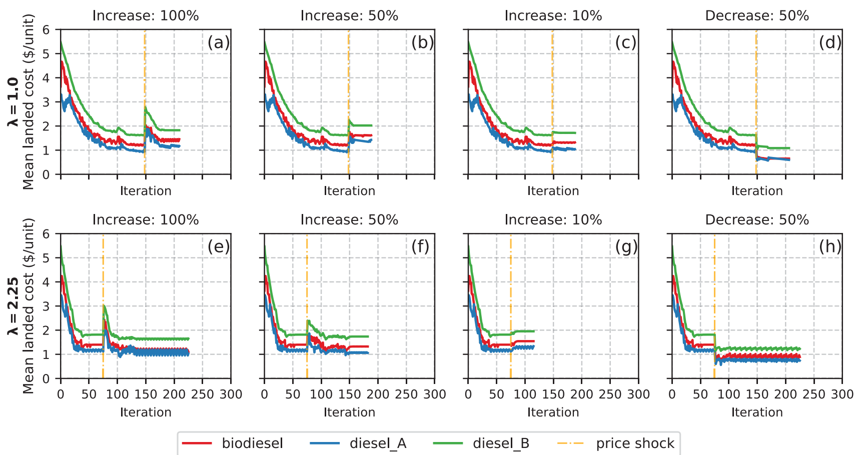

Fig. 4. Evolution of mean landed costs before and after price shocks of $+100\%$, $+50\%$, $+10\%$, -50% applied to all sellers, over 150 iterations, for loss-neutral buyers ($\lambda = 1.0$) in panels (a)-(d) and loss-averse buyers ($\lambda = 2.25$) in panels (e)-(h).

permanently lower equilibrium values. This has to do with how the intermediate supply chain agents, the distributors, lower their reservation prices, making it difficult to return to higher price levels later.

Also in Fig. 4, contrasting loss-neutral ($\lambda = 1.0$, panels a–d) and loss-averse ($\lambda = 2.25$, panels e–h) buyers indicates distinct recovery dynamics, particularly under extreme perturbations and exposes the instability in loss-averse markets.

Under the $+100\%$ price shock (panels a and e), loss-neutral markets ($\lambda = 1.0$) exhibit controlled adjustment: landed costs rise sharply at the shock point, then with slight more than 50 iterations converge back toward equilibrium. The $\lambda = 2.25$ market, by contrast, shows pronounced oscillatory behavior that persists throughout the entire 150-iteration observation window.

Similar patterns emerge in the 50% decrease scenario (panels d and h): loss-averse agents dramatically overreact to the reduced prices, generating volatile price adjustments that fail to stabilize within the simulation period. This oscillatory instability is absent in the loss-neutral case, where prices smoothly adjust to the new market conditions.

4. Discussion

4.1. *Model findings and interpretation*

This model demonstrates that incorporating loss aversion into buyer decision-making produces measurable effects on market equilibrium and dynamics. In the baseline case, loss-averse agents achieve convergence 2–3 times faster than loss-neutral agents (45–65 vs. 130 iterations), driven by rapid anchoring to reference prices and reduced willingness to switch suppliers when faced with perceived losses. This acceleration in convergence is a direct consequence of the loss aversion utility function and greedy assignment algorithm used here.

Under price shocks, the model exhibits contrasting dynamics between loss-neutral ($\lambda = 1.0$) and loss-averse ($\lambda = 2.25$) scenarios. Loss-neutral agents converge smoothly to new equilibria, while loss-averse agents show persistent oscillations that do not stabilize within 150 iterations (Fig. 4). This behavior arises because agents with loss aversion resist departing from reference points, creating conflicting incentives when shocks exceed a threshold magnitude.

These results are specific to the spatial competition structure, parameter values ($\lambda \in \{1.0, 1.5, 2.0, 2.25\}$), initial conditions, and algorithm design of this model. Different initial prices, network topologies, or reference-point update rules may produce different outcomes. The oscillatory behavior observed under extreme shocks ($+100\%$) suggests that loss aversion's effects are not uniformly stabilizing but depend critically on shock magnitude and the degree of displacement from baseline reference prices.

4.2. *Connection to prior work and methodological contribution*

Our baseline result—that loss aversion raises equilibrium prices by 11.6%—aligns with prior behavioral economics literature (Heidhues and Kőszegi, 2008; Karle and Peitz, 2014). However, those studies typically examine static or quasi-static markets. By embedding loss aversion in a dynamic agent-based model with explicit supply chain structure, we add a methodological tool for exploring how bounded rationality interacts with market topology, capacity constraints, and temporal dynamics.

The 2025 ESREL study (Duque et al., 2025) used rational-actor assumptions. This extension demonstrates how loss aversion can be incorporated into such frameworks and highlights that behavioral parameters have non-trivial effects on both convergence speed and shock response. Extensions might integrate loss aversion with contractual constraints, incomplete information, and agent learning in order to increase realism.

4.3. *Model limitations and future directions*

Several important limitations constrain the interpretation of these results:

Information and initial conditions: Agents have perfect information; results may differ substantially with information asymmetries or different initial price distributions.

Reference point specification: Using only the most recent transaction as the reference point is a simplification. Real agents may anchor to longer-term averages, contractual prices, or industry benchmarks.

Network structure: Results apply to this three-echelon spatial configuration with the given capacities. Other supply chain topologies may exhibit different dynamics.

Future work should examine other forms of convergence algorithms that are faster and more stable to initial conditions, and compare outcomes across different network structures and shock scenarios. Empirical validation using transaction-level fuel market data would help calibrate model parameters and test whether the model's predicted dynamics match observed behavior during disruptions. Integration with contractual and multi-period relationships, alongside with the possibility of coordination between supply-points (e.g. a supplier that owns more than one refinery) would improve realism and utility for policy evaluation.

5. Conclusion

This paper develops a method for incorporating loss aversion—a key feature of bounded rationality—into agent-based supply chain models. The modeling exercise shows that loss aversion parameters affect both baseline convergence speed and transient response to price shocks. Specifically, higher loss aversion accelerates equilibration but can produce oscillatory behavior under extreme perturbations, depending on initial conditions and shock magnitude.

The model provides a foundation for future policy evaluation. As supply chain disruptions become more frequent, tools that allow policymakers to simulate market response under various behavioral and regulatory scenarios become increasingly valuable. This work demonstrates that behavioral mechanisms can be embedded explicitly in spatial competition models, enabling more nuanced exploration of how agent decision-making influences supply chain dynamics.

Future extensions should address the limitations noted above and test the model's predictions against empirical data from actual disruption events. Integration with contractual constraints, coordination among suppliers, and multiple behavioral mechanisms will be necessary to support policy recommendations. The framework offers a starting point for this broader research agenda.

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