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A managerial operationalization of antifragility and its consequences in supply chains

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Abstract
Robust systems can recover after a shock to a previous steady state. Thus, to make organizations robust is a frequent goal of system dynamics projects. However, in recent years, the adequacy of robustness as a design criterion for systems (and, thus, of the models that represent them) has been challenged based on the ideas of antifragility, that is, the ability of a system to recover after a shock and to achieve a higher performance level than before the shock. The purpose of this article is to propose how antifragility can be interpreted and operationalized in managerial settings and to explore what consequences result from its existence for supply chain behaviour and performance. System dynamics modelling and simulation are employed, and the insights of the analyses are used for a critique of the antifragility concept. It is demonstrated that the antifragility concept can lose its unambiguous advantage in highly dynamic situations.

KEYWORDS
antifragility, simulation, supply chain, system dynamics

1 | INTRODUCTION

System dynamics is about endogenously explaining the behaviour of a system by its structure (Forrester, 1968; Richardson, 2011). The purpose of providing such structural explanations is to achieve robust system behaviour in which the system performs as well as the circumstances allow and in which it can recover from shocks (Coyle, 1996). The robustness of a system can be assessed and improved by developing formal structural models and conducting simulations, including scenarios and sensitivity analyses (Sterman, 2000). Based on such simulation experiments, potential adaptations of the system can be tested, and structural or policy changes can be recommended to improve its robustness. If a system's behaviour shows a satisfactory response to external shocks and is insensitive to changes in its parameter values within a plausible range, the system is categorized as robust (Moxnes, 2005; Sterman, 2000).

Taleb (2007) claimed that such a robustness approach in modelling leads to misplaced trust in the actual robustness of a real system. He argued that modellers (very likely, although not explicitly mentioned, including system dynamicists) tend to assume a Gaussian probability distribution of external shocks and base their analysis on this type of probability distribution when testing for robustness. In doing so, they focus on the ordinary or the average instead of investigating extreme exceptions. Thus, in Taleb (2012), he introduced the concept of 'antifragility' as an alternative system characteristic to robustness. Antifragility refers to systems that gain from volatility and disorder and show an improvement in performance when subjected to large and seemingly implausible changes in parameters.[1] Antifragility encompasses robustness as it means the ability to recover after a shock, however, with the addition to achieve an even higher performance level afterwards.

De Bruijn et al. (2019) argued that system dynamics models not only need to possess the robustness system characteristic but also can be antifragile. In that paper, they also show an abstract and prototypical structure of an antifragile system dynamics model. Extending that work, the purpose of this article is to explore how antifragility could operate in a supply chain setting as an example of a structurally complex system: how antifragility can be operationalized based on managerial considerations and what consequences for behaviour and performance of the chain result from it being antifragile. However, it is not the purpose of this exploratory study to discuss the existence of antifragility in principle or to provide a causal justification—for these, the reader is referred to Taleb's (2009, 2012) works or the de Bruijn et al. (2019) paper, respectively.

Methodologically, this study employs system dynamics modelling and simulation; as a study case, an illustrative linear four-tier supply chain model is used. The simulation experiments will exemplify that the theoretical superiority of antifragility compared with robustness becomes less clear once we assume reasonably high levels of ambiguity (e.g. regarding performance measures), structural complexity (like highly dependent and interacting agents) and dynamics (like performance feedback).

The structure of this article is as follows. In the next section, robustness and antifragility are introduced in more detail; a managerial operationalization of antifragility is provided. In the section thereafter, two variants of a standard system dynamics model are presented that show robustness and antifragility, respectively. Afterwards, the results of these model variants are compared, and the model is further extended to alleviate some of its assumptions. Before the paper is concluded, the significance of the simulation results for the concept of antifragility and for managing supply chains is discussed.

2 | A MANAGERIAL OPERATIONALIZATION OF ANTIFRAGILITY

Robustness was already recognized by Senge and Forrester (1980) as an important characteristic of dynamic systems. A system is classified as robust if it (i) shows satisfactory responses when subjected to a wide variety of inputs; (ii) performs satisfactory over the range of parameter values considered plausible; and (iii) is relatively unaffected by a considerable amount of noise usually found in socio-economic systems. Hence, a robust system shows no significant changes in behaviour patterns when it is subjected to shocks. In a robust system situated in the normally distributed space of exogenous shocks (regarding frequency and strength), the reaction function is characterized by gains and losses cancelling out over time. This means that a robust system possesses an outcome probability distribution that is centred around the mean and characterized by thin left and right tails. However, reality often shows that systems that initially appear to be robust at some point in time are affected by outlier events such as Black Swans (Taleb, 2012). In other words, a system might seem to be robust in the short run—because it has been exposed to normally distributed randomness only—when in fact it is affected in the long run as developments over time often show not normally distributed randomness (Taleb, 2007).

Although not using the term (which had not been invented back then), it probably was Coyle (1977, as cited in Coyle, 1996) who made one of the first references to the mechanism of antifragility. He noted that ‘a managed system should be able to defend, recover from, and create and *exploit* shocks’ (p. 6, italics added). The inclusion of benefitting from shocks is crucial here as it implies that a system might not only absorb shocks—and therefore being robust—but also can exploit shocks and be what later has been called ‘antifragile’. Technically speaking, such an antifragile system is characterized by a positive convex-asymmetric reaction function to external shocks (i.e. overproportional gains from shocks). In other words, randomness impacting both positive and negative on the initial system's level leads to more gains than losses. This means that for the antifragile system, the gains are always bigger than the losses notwithstanding the size of the randomness impacting on the system (Taleb, 2012). Such a system that benefits from randomness is characterized by long-term survival.

In a first economic approximation, this study assumes antifragility to trigger an effect like the experience curve, which is a widely applied concept in strategic and operational management (Day & Montgomery, 1983; Henderson, 1984). Empirical evidence for experience curve effects is well documented (Yelle, 1979), dating back to Wright (1936). For several industries, it could be shown that average unit costs can be reduced by a certain percentage each time accumulated production doubles. Thus, in its standard formulation, accumulated production volume serves as a measure for the firm's experience. In the context of this paper, however, experience could come with volatility in the environment, not with the

[1]Taleb (2012, tab. 1) provided a rather eclectic list of examples of potentially antifragile systems, for example, Hydra in Greek mythology, entrepreneurs, sports exercises in real-world settings (not the gym), venture capital, artists, hormesis in the human body or taxi drivers.

mere increase of production volume. Consequently, it is proposed that an antifragile system would be able to benefit from experiencing external shocks and perform subsequently on a higher level owing to internal adaptation processes caused by the shocks.

In the literature, a few factors causing the experience curve effect have been identified (Alberts, 1989; Day & Montgomery, 1983; Hax & Majluf, 1984). These factors can be grouped into three major clusters, which apply in an equivalent way to antifragile systems: learning effects, product and process improvements, and economies of scale. External shocks might lead to learning effects by members of the organization; they might induce improvements in the way processes are designed and what type of product or service is provided; and they might lead to investments into scaling-up capacity that could result in higher performance in the future. In the subsequent modelling of a supply chain, the notion of representing antifragility by a mechanism similar to the conventional experience curve is used to compare its behaviour with a merely robust version of the chain. So the purpose is not to causally model how learning and improvement lead to antifragility but rather to explore potential consequences, once we assume antifragility to work like an experience curve effect.

Usually, the experience curve effect is formulated in the following way: whenever accumulated production doubles, average per unit costs (deflated, real costs) decrease $1-p$ %; we then speak of a 'p % experience curve' (Boston Consulting Group, 1970). Mathematically, the experience effect is described by the following equation:

$$c_t = c_0\left(\frac{X_t}{X_0}\right)^{-\ln p/\ln 2}, \tag{1}$$

where c_t stands for the cost of each unit in period t and c_0 for initial unit costs; X_t and X_0 represent accumulated production volumes until period t or in the first period observed, respectively; and p is the experience coefficient.

Similarly, an experience effect based on external volatility (which is here interpreted as antifragility) is operationalized as

$$c_t = c_0\left(\frac{E_t}{E_0}\right)^{-\ln a/\ln 2}, \tag{2}$$

where c_t stands for a cost factor in period t and c_0 for initial costs; E_t represents accumulated absolute changes of an external input variable E to the system until period t; E_0 is the baseline value of this external input in the first period observed; and a is the antifragility coefficient that determines what the new relative cost level is after a doubling of the external input (i.e. with each doubling cost are reduced by $1-a$).

Note that depending on the case, E can represent many different factors potentially causing a shock to the system, for instance, changes to the number of competitors, the number of product substitutes available, or the number of new product generations available. In the modelling example hereafter, changes of end customer demand of a supply chain (as the only external input to that system) is used. Regardless of the causes of the shock, it leads to subsequent adaptation in the internal structures and processes of the organization that allows it to proceed with lower cost levels and, thus, increases business performance. This interpretation is also the reason why upward and downward changes are expected to have a positive effect on costs because with both types of variety comes a chance for adaptation (which is different to the experience curve where accumulated production volume obviously cannot shrink).

With the experience curve effect, this operationalization of antifragility shares the aspect of potentiality: neither cost reductions based on experience nor based on external shocks will result necessarily, as if it was a natural law. Rather, there is the potential for cost reduction or performance increases when the organization is ready and capable to exploit the possibility. This is also the reason why, of course, many organizations are more hampered than helped by changing external conditions—antifragility is not a consequential reaction coming from change but a potential that needs to be reaped.

In this study, it is assumed that increases and decreases of end customer demand lead to adaptations in the order fulfilment functions of logistics companies that allow these companies to lower their inventory cost levels and, thus, reap the potential of antifragility.

3 | A SUPPLY CHAIN MODEL TO ANALYSE EFFECTS OF ROBUSTNESS AND ANTIFRAGILITY

Simulation experiments to capture the differences between robust and antifragile systems are conducted with a system dynamics model (Forrester, 1961; Sterman, 2000) of a supply chain. Based on a model by Kirkwood (1998), the model represents the structure of the beer distribution game (Senge, 1990), that is, a four-tier sequential supply line; Figure 1 shows the stock-flow diagram with identical structures for the four supply tiers: retailer, wholesaler, distributor and factory. Regarding those elements that exist in the regular beer distribution game, the model follows a parametrization as indicated by Sterman (1989). In particular, order decisions are modelled in accordance with his behavioural model of ordering in the beer distribution game, which is based

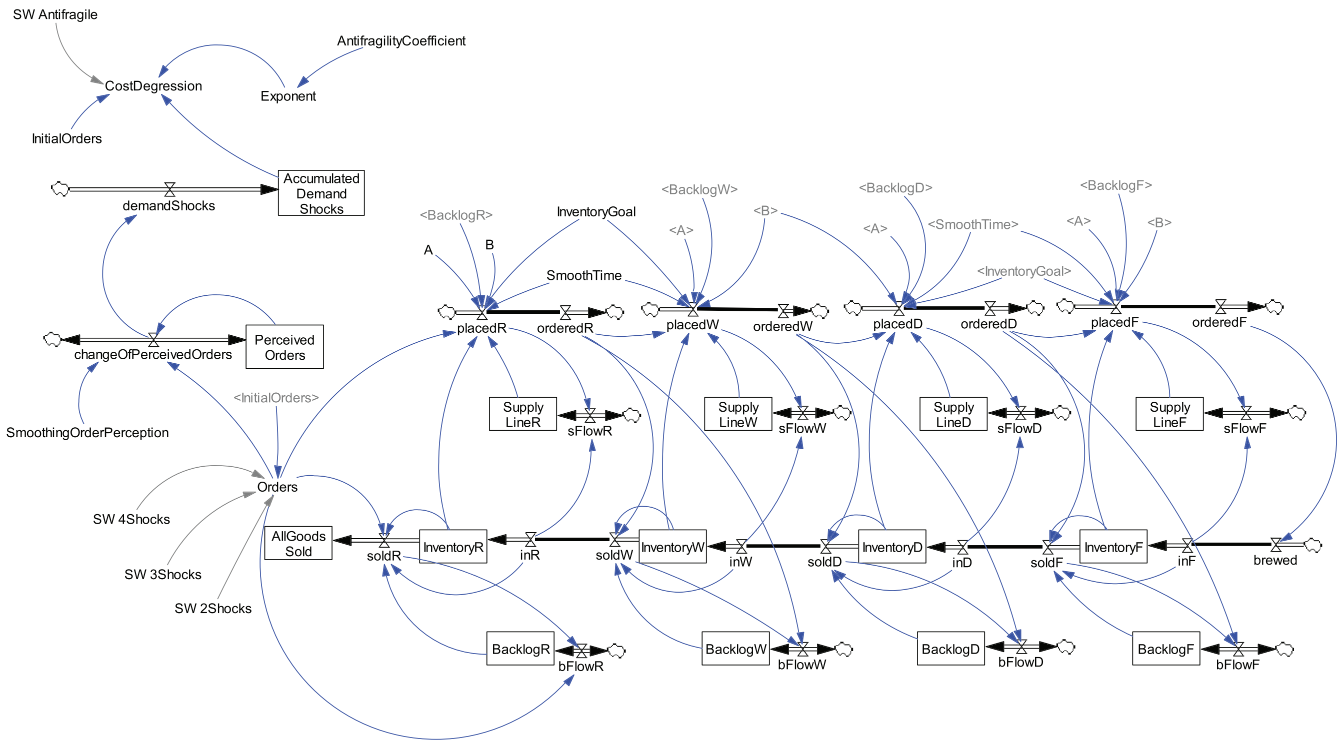

FIGURE 1 Stock-flow structure of first version of simulation model used; based on Kirkwood (1998) [Colour figure can be viewed at wileyonlinelibrary.com]

on an anchoring-and-adjustment strategy (Tversky & Kahneman, 1974).

Extensions to Kirkwood's original model are the structure on the upper left (dealing with accumulating the absolute value of external volatility as discussed in the previous section) and structures to calculate performance indicators of individual tiers as well as the total supply chain (not shown in the diagram). To keep track of accumulated external shocks and to calculate the resulting cost decrease, in the stock *PerceivedOrders*, a smoothed average of historical orders is stored; with a *SmoothingOrderPerception* equal to 1, this just keeps track of any changes in *Orders*. The absolute values of all changes to orders are then used for calculating *AccumulatedDemandShocks* and, according to Equation 2, the cost effect of order volatility (*CostDegression*). This cost degression factor determines the height of inventory costs that are initially \$0.5/week/case but can decrease when the system is antifragile and hit by a shock. The antifragility coefficient is set to 0.95 in all models. That is, with each doubling of customer demand, costs of inventory go down by 5%.[2]

Note that with this structural extension, the supply chain is treated as one entity, that is, all tiers respond to the external shock of changing end customer demand, and the degree of antifragility is the same throughout the chain (cost degression is the same for all stages). Furthermore, the level of costs does not feed back on any other decision in the supply chain. *SW Antifragile* is a binary variable: if 0, the structure calculating cost decreases based on changes to customer demand is not active; if 1, the model is supposed to show antifragility.

System behaviour is explored in simulation runs over 200 weeks, with a simulation time step of 0.03125 and using Euler integration. As Figure 2 shows, customer

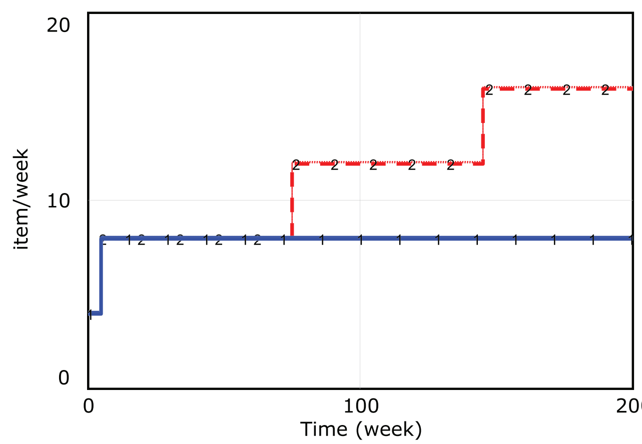

FIGURE 2 End customer orders (=external input into the system) over time for simulation runs with one shock in Week 5 (1, blue, solid line) and three shocks in Weeks 5, 75 and 145 (2, red, dashed line) [Colour figure can be viewed at wileyonlinelibrary.com]

[2]This is a plausible but rather modest value as compared with the usual experience curve rates found in industry, which are between 10% and 25% (Hax & Majluf, 1982); the value serves illustrative purposes only.

orders (as external input into the system) are four items in the beginning and in Week 5 increase to eight items (as in the regular beer distribution game). In order to study long-term effects of repeated exogenous volatility, also scenarios with three demand shocks are tested. Note that in both cases, only step increases in customer orders are used; abrupt decreases or other demand patterns need to be studied in future research (as an example, Appendix A provides simulation results for a demand decrease back to 4 in Week 75 and down to 0 in Week 145).

4 | BEHAVIOUR AND PERFORMANCE OF ROBUST AND ANTIFRAGILE SUPPLY CHAINS

In this paper, three sets of simulation experiments are conducted. For all experiments, two different customer demand scenarios (representing the external shocks to the system) are considered (see Figure 2). First, the results of a robust supply chain are compared with an antifragile supply chain. The second set of experiments compares the antifragile supply chain with another, also antifragile chain for which performance influences subsequent operational decisions (ordering of supply at the supply chain tiers); that is, feedback of performance on operations is analysed. While in the first two experiments the supply chain is treated as one entity, this assumption is alleviated in the third analysis. For this, it is assumed that all supply chain tiers have independent ordering and cost degression mechanisms that are driven by end customer demand for the most downstream tier (the retailer) only; other supply chain tiers take downstream orders as their external input.

4.1 | Experiment 1: Comparing a robust with an antifragile supply chain

Figure 3 shows the operational behaviour of the model for a one-shock (left) and three-shock (right) situation. In the figure, the volatile behaviour of effective inventory for the four tiers in the supply chain is depicted, that is, inventory level minus backlog. The graphs show the typical bullwhip effect in supply chains where order variance (and, thus, oscillations of inventory levels) is amplified upstream the chain, that is, from retailer to factory, as it usually can also be observed when playing the beer distribution game (Forrester, 1961; Lee, Padmanabhan, & Whang, 1997; Senge, 1990). For this version of the model, there is no difference between the robust and the antifragile system simulation regarding operational behaviour, because antifragility only influences cost (via the mechanism specified in Equation 2). Although ordering decisions influence costs, there is no feedback from cost to the operational parts of the model; in particular, orders are not influenced by cost levels.

Figure 4 depicts the development of total costs of the supply line for robust and antifragile chains (for both a one-shock scenario and a three-shock scenario and a 95% antifragility coefficient), which is a combination of inventory (initially, \$0.5/item/week) and stock-out costs

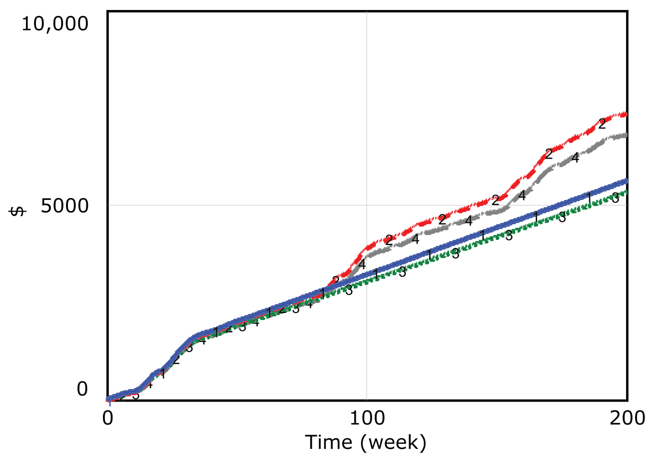

FIGURE 4 Comparison of total accumulated cost for a robust and an antifragile supply line (note that lower costs are beneficial): robust/one shock (1, blue, solid), robust/three shocks (2, red, dashed), antifragile/one shock (3, green, dotted) and antifragile/three shocks (4, grey, long dashes) [Colour figure can be viewed at wileyonlinelibrary.com]

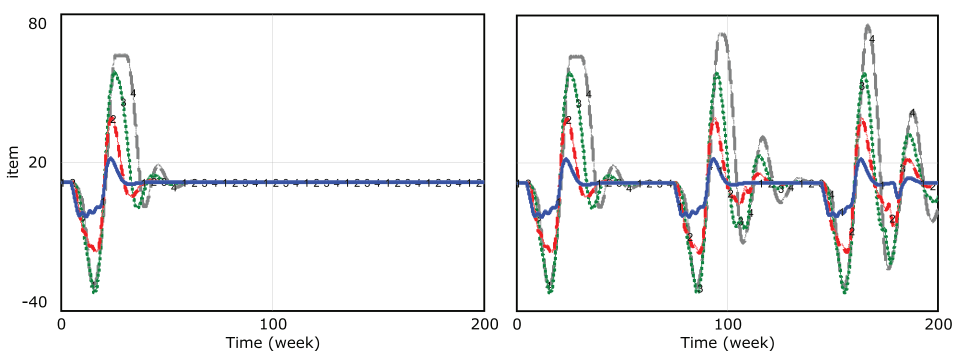

FIGURE 3 Effective inventories for a robust and an antifragile supply line. Left, as a result of one demand shock in Week 5; right, as a result of three demand shocks in Weeks 5, 75 and 145 (cf. Figure 2): retailer (1, blue, solid), wholesaler (2, red, dashed), distributor (3, green, dotted) and factory (4, grey, long dashes) [Colour figure can be viewed at wileyonlinelibrary.com]

($1/item/week). Note that lower costs are beneficial and that overall accumulated cost cannot decline. Not surprisingly, robust scenarios result in higher costs than corresponding antifragile scenarios because only the antifragile system allows for cost coefficients to decline owing to demand shocks. Thus, with more shocks, the antifragile case becomes more and more favourable as compared with the robust system. However, overall cost performance is largely determined by the effect of demand shocks on operational performance (cf. Figure 3); so the antifragile supply chain with three demand shocks still scores worse than the robust supply line with just one shock. Only when the value of the antifragility coefficient is 82% or smaller can an antifragile supply chain facing three demand shocks achieve better cost performance than the robust chain with one shock only (a sensitivity test of the antifragility coefficient can be found in Appendix A).

Because the simulation results so far were expected given the conceptualization of the model (and, thus, serve as validation runs only), two important assumptions of the model will be discarded in the remainder of this section: (i) the assumption that costs (and, thus, antifragility) do not affect operational decisions and (ii) the assumption that the supply chain is one entity with one external input only (customer demand) that influences cost coefficients of all supply chain tiers in the same way.

4.2 | Experiment 2: Performance feedback on subsequent ordering

Regarding the weakening of the first assumption (performance does not influence behaviour), the model is slightly extended in order to implement a feedback relationship between costs and operations. More concretely, the inventory cost level is used to determine the operational safety stock level and, thus, order rates at the four tiers. For that, the ratio of the norm inventory cost level ($0.5/item/week) and the actual inventory cost level (which can only be lower than the initial level owing to the antifragility effect) modifies the safety stock level (originally, items in each supply tier inventory). The rationale behind this modification is that lower inventory costs allow for higher safety stock without giving up profitability. The ratio of the two cost levels is used in a table function, accounting for the degree of service-level orientation that a company has (i.e. how certain they want to fulfil demand): the higher it is, the more are lower inventory costs used to stock up inventories.

In Figure 5, the effects of this model extension are compared with the antifragile model with no feedback, which has been used before for one and three demand shocks. The graph of average effective inventories (left) shows that indeed the feedback between inventory costs and ordering leads to slight differences in operational behaviour. As expected, supply lines with a connection between costs and ordering show higher inventory levels than those without when the supply line is in balance, as the model was formulated in that way. Supply lines with higher inventory levels result in a higher service level, caused by less stock-out situations, which is assumed to be a goal of the companies in this supply line. However, as the graph of total costs (right) indicates, high stock levels and correspondingly high service levels are not always beneficial in terms of costs, in particular—as is the case in this example—when not many stock-out situations occur. For the one-shock scenarios, the higher inventory levels and the resulting costs clearly overcompensate for gains from the antifragility effect. For the three-shock scenarios, this also is true for most of the simulation period. However, at the very end and after the third external shock (being another increase in demand), a higher safety stock level (and related higher inventory costs) is roughly outweighed by lower backlog costs, resulting in very similar costs for the two supply chains.

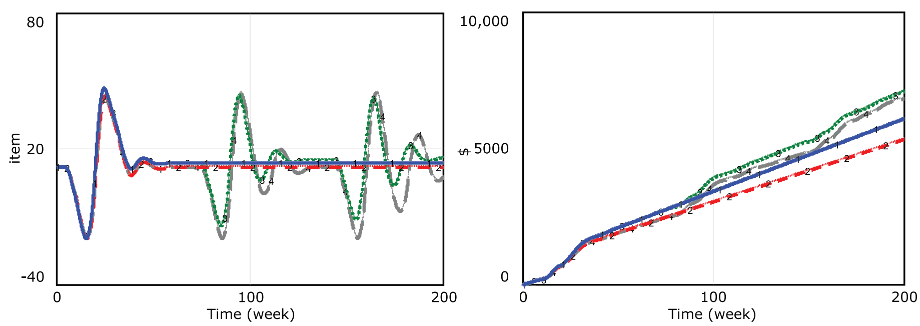

FIGURE 5 Comparison of two antifragile supply lines (one with performance feedback and one without). Left, average effective inventories; right, total accumulated costs (note that lower costs are beneficial): antifragile with performance feedback/one shock (1, blue, solid), antifragile/one shock (2, red, dashed), antifragile with performance feedback/three shocks (3, green, dotted) and antifragile/three shocks (4, grey, long dashes) [Colour figure can be viewed at wileyonlinelibrary.com]

4.3 | Experiment 3: Supply chain tiers as independent entities

For the last set of simulation experiments, the assumption is given that the whole supply chain acts as one entity; that is, that ordering at each stage depends on the same antifragility mechanism. Rather, in this version of the model, each tier experiences separate demand shocks—resulting from the orders of the downstream supply stage—and calculates cost degression by antifragility and its effect on ordering independently. To achieve this, the model substructures representing the antifragility mechanism and ordering policies, which existed once in the model so far only, are replicated for each supply chain tier.

Figure 6 depicts a comparison for supply chain behaviour of this version with the previous model, partially already shown in Figure 5. As supply chain management would suggest, if the supply chain acts as one entity (previous model version), it results in better cost performance than when the tiers decide in isolation, because supply chain stages optimize their local ordering and, thus, their individual performance (right). Also, on the operational level, one can see that separated decision making leads to slightly higher oscillations regarding effective inventories than the corresponding integrated supply chains (left).

Comparing a robust versus an antifragile version of this last version of the model reveals that for robust versus antifragile supply chains with separated decision making, other outcomes result as compared with integrated supply chains (cf. Experiment 1). Figure 7 (right) demonstrates that in the one-shock scenario, the robust supply chain performs better regarding total cost than the antifragile chain. For the three-shock scenario, at least towards the end of the simulation period, the antifragile system scores better. These results are corroborated by the operational behaviour of the different chains (Figure 7, left): for one demand shock, the antifragile chain results in a permanently too high inventory level; for three demand shocks, the robust system results in stronger volatility regarding operational behaviour.

To summarize the findings from the three simulation experiments, Table 1 lists total supply chain cost and the normalized standard deviation of effective inventories as a measure for the operational performance of the chain. With this operational measure, the volatility of the

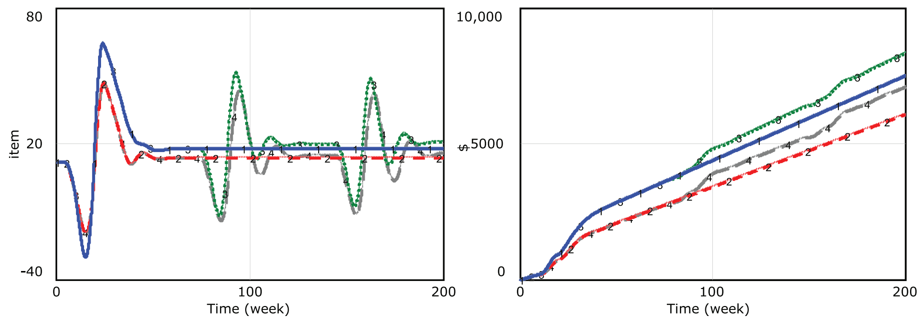

FIGURE 6 Comparison of two antifragile supply lines (both with performance feedback), one with decentralized decision making and one with centralized decision making. Left, average effective inventories; right, total accumulated costs (note that lower costs are beneficial): antifragile decentralized/one shock (1, blue, solid), antifragile centralized/one shock (2, red, dashed), antifragile decentralized/three shocks (3, green, dotted) and antifragile centralized/three shocks (4, grey, long dashes) [Colour figure can be viewed at wileyonlinelibrary.com]

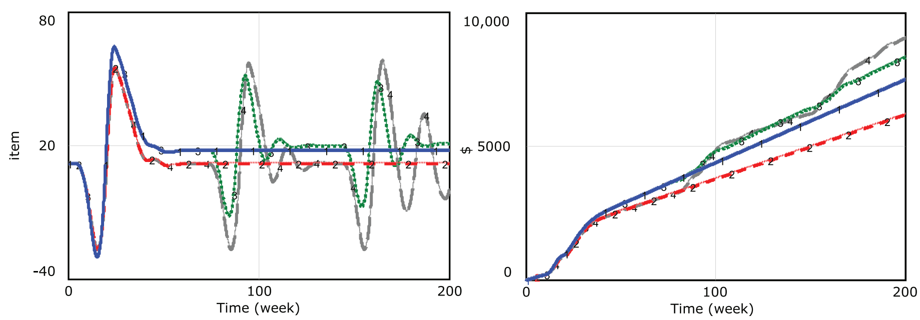

FIGURE 7 Comparison of a robust and an antifragile supply line (both with performance feedback and separate decision making). Left, average effective inventories; right, total accumulated costs (note that lower costs are beneficial): antifragile decentralized/one shock (1, blue, solid), robust decentralized/one shock (2, red, dashed), antifragile decentralized/three shocks (3, green, dotted) and robust decentralized/three shocks (4, grey, long dashes) [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Summary of cost and operational performance of the simulation experiments (for both indicators, smaller values are preferable)

No. of demand shocks	Nature of supply chain	Total supply chain cost (end of simulation) ($)	Normalized standard deviation of effective inventories (*dmnl*)
1	Robust	5,615	0.666
	Antifragile	5,341	0.666
	Antifragile with performance feedback	6,104	0.608
	Antifragile with performance feedback and separate decision making	7,526	0.681
	Robust with performance feedback and separate decision making	6,209	0.835
3	Robust	7,372	1.281
	Antifragile	6,833	1.281
	Antifragile with performance feedback	7,108	0.916
	Antifragile with performance feedback and separate decision making	8,360	0.817
	Robust with performance feedback and separate decision making	9,080	1.429

resulting behaviour is emphasized. Furthermore, a distinction is made regarding scenarios with one or three shocks of end customer demand.

5 | DISCUSSION OF SIMULATION RESULTS

Taleb's idea of antifragility is a powerful concept that has widely attracted interest. Albeit rather abstract in its principal form as a general system characteristic, it promises desirable features: it combines a beneficial response to volatility and uncertainty with the prospect of improved performance of the system. Although Taleb (2012) also presented a series of real-life examples, his main ideas are derived from financial markets and investments therein. In some respect, that setting is relatively simple: there is one performance measure (return on investment or profit) that hardly reciprocally affects the working of the market; only one decision needs to be made (investing or not) by an atomistic investor who does not as an individual has a big influence on the working of the market; and one entity exists that determines outcomes (the market). However, in organizations and supply chains (or networks of organizations), complexity and dynamics might make it difficult to apply and reap the potential benefits of antifragility because those simplifying characteristics are not prevalent: there are usually more than one, often conflicting performance measures at work whose values dynamically influence the future state of the organizations; in some industries and for some supply chains, there are clearly dominant players whose decisions change the structure of the industry or supply chain; the outcome of decisions is dependent on a variety of other players' decisions and complex relationships between them.

The three simulation experiments in this paper illustrate these issues based on a system dynamics model of the beer distribution game. In particular, the simulations provide three points of contextualization, where the concept of antifragility would benefit from further clarification when it comes to complex and dynamic settings.

First, Experiment 1 showed, although in a simple way, that usually more than one possible performance measure exists in real-world systems. Furthermore, these indicators might be contradicting each other, be in a trade-off relation or be of different importance depending on the situation. In the simulations, financial performance in terms of total supply chain cost was beneficial for the antifragile as compared with a robust version of the chain. However, operational performance (measured here as effective inventories) showed severe oscillations in both cases caused by the ordering policies that are used—in particular for the three-shock scenario. Thus, the antifragility characteristic might lead to efficiency gains (e.g. cost savings) when actually the fundamental working of the system is at stake (owing to strong fluctuations threatening the principal function of operations).

Second, usually systems are including feedback from performance to operations (here inventory cost to ordering) once we apply a dynamic perspective. Given the strength of this feedback and the context of the situation, a better performance level achieved by antifragility might affect decision makers in future decision processes; in the simulations, lower inventory costs allowed decision makers to adapt their ordering policies, resulting in higher inventory levels. Once we assume such performance feedback, antifragility is not anymore superior in general; its superiority depends on contextual factors (here the number of demand shocks) and their development over time. This issue was illustrated by Experiment 2.

Third, when antifragile components of a system are coupled, local optimization at the expense of overall system performance could happen that would bring the system into an unfavourable situation compared with a purely robust system if not triggered from the outside (here by customer demand shocks). Experiment 3, in which this issue was explored, showed that despite more favourable inventory costs in the antifragile supply chain, overall costs are higher as compared with a robust but otherwise similar chain, when there are not many external shocks.

In summary, the complexity and dynamics of the model investigated contextualize the at-first-glance general benefit of antifragility as compared with robustness. Although beneficial in many of the scenarios tested, by no means, antifragility is always favourable—in particular when one considers reasonable extensions to the model like performance feedback and decentralized decision making in the supply stages. Whether system designers should therefore try to implement antifragility in real supply chains (e.g. by establishing organizational learning mechanisms that take advantage of changes in the environment; these could result in more flexible procedures, so the supply chain becomes more responsive to customer needs) depends to a high degree on their assumptions about future volatility external to the chain.

6 | CONCLUSIONS

Starting from the assumption that antifragility is a relevant system characteristic, the purpose of this paper was to provide a managerial operationalization of the concept and, based on this, explore consequences of antifragility in a supply chain setting. Antifragility was operationalized as an experience curve-like phenomenon, and its consequences were tested with the help of a system dynamics model of a four-tier supply chain, structurally similar to the well-known beer distribution game. On the basis of this model, three simulation experiments were conducted that emphasized the difficulty of interpreting antifragility in complex dynamic settings. A set of inconsistent performance indicators, performance feedback on decision making and behaviour, and the interdependence of separate decision-making units were identified as causes of this difficulty and illustrated by the simulations.

Admittedly, these insights were gained based on a rather specific modelling case of a supply chain. Thus, the particular simulation results depend on its characteristics, like the structure of the supply chain, the ordering policies used, the development of demand as external shock and the non-existent capacity constraints. Furthermore, some results only show marginal numerical differences that are interpreted here (partially caused by the cautious assumptions regarding the strength of the antifragility effect). All these assumptions can and should be addressed in future studies. However, the current study demonstrates that antifragility as a desired system characteristic needs to be scrutinized (or contextualized) once we assume higher levels of complexity and dynamics as in many financial studies.

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APPENDIX A.

This appendix provides the results of two additional simulations. Figure A1 shows accumulated cost when end customer demand decreases in Week 75 back to the initial value of four and in Week 145 to zero cases. These runs are produced with the first model version that does not contain performance feedback or decentralized decision making (which also means that there are no differences in effective inventories for robust and antifragile models). The antifragile model version shows cost benefits also for downward developments of demand. As a comparison, the results of the three-shock scenario with only upward demand changes are included (see also Figure 4), although direct contrasting of the results based on these two demand patterns requires careful interpretation. A comprehensive investigation of the effects of different demand patterns requires further study.

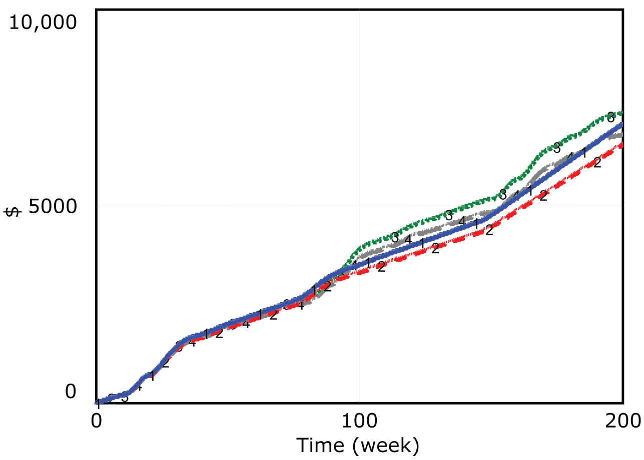

FIGURE A1 Comparison of total accumulated cost for a robust line and an antifragile supply line with one upward and two downward demand shocks; for further contrast, the total accumulated costs for three upward shocks are included (see also Figure 4) (note that lower costs are beneficial): robust/up and down (1, blue, solid), antifragile/up and down (2, red, dashed), robust/three shocks (3, green, dotted) and antifragile/three shocks (4, grey, long dashes) [Colour figure can be viewed at wileyonlinelibrary.com]

Figure A2 shows the output for accumulated cost of a sensitivity run, varying the antifragility coefficient uniformly from 0 (i.e. cost going down proportionally with demand changes) to 1 (i.e. not antifragility effect; equals a robust supply chain). Performance is mostly better (i.e. lower parts of the graph) than the costs achieved with the relative cautious value of 0.95 for the antifragility coefficient or, consequently, for a robust supply chain.

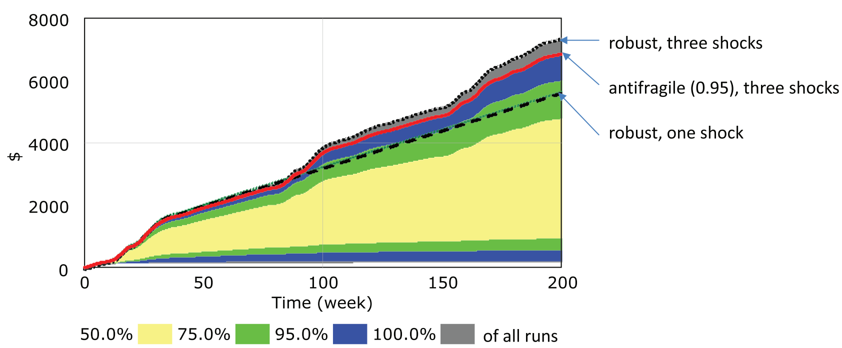

FIGURE A2 Development of total accumulated cost in a sensitivity run for *AntifragilityCoefficient* (uniform distribution between 0 and 1) and comparison with robust simulations (cf. Figure 4) [Colour figure can be viewed at wileyonlinelibrary.com]