

Resilience in Motion: A Framework for Mitigating Global Supply Chain Disruptions in the Post-Pandemic Era

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Abstract: The COVID-19 pandemic exposed the fragility of globally optimised, lean supply chains, and the shocks that followed, including the war in Ukraine, port congestion and regional conflicts, have shown that disruption is now a recurring condition rather than an exceptional event. This paper proposes Resilience in Motion, a five-stage framework (Sense, Absorb, Adapt, Recover and Learn) for mitigating global supply chain disruptions in the post-pandemic era. The framework is grounded in a taxonomy of four disruption categories (direct outbreak effects, policy-induced disruptions, behaviour-induced disruptions and strategy-induced disruptions) and in an analysis of the Global Supply Chain Pressure Index, which shows that the pandemic-era peak exceeded four standard deviations above the long-run average, more than four times the level recorded in the global financial crisis. We formalise the framework with models of severity, safety stock under lead-time uncertainty, the bullwhip effect, supplier concentration, ripple-effect propagation and a composite resilience score. The framework was evaluated by simulating a four-tier, 60-node global network under four disruption scenarios, one for each category, and comparing a lean single-sourced baseline with buffer inventory, dual sourcing, regionalisation, digital visibility and the integrated framework. In the factory-shutdown cascade scenario the baseline fill rate fell to 41% and needed 26 weeks to recover, whereas the integrated framework limited the fall to 86% and recovered in 7 weeks. Each single strategy cost more than it saved in expected terms, while the integrated framework reduced total expected cost by 5.3%. The findings indicate that resilience results from coordinated, complementary measures rather than from any single lever, and that the cost of building it is repaid through the avoided losses of disruption.

Keywords: *Supply Chain Resilience, Global Value Chains, Post-Pandemic Disruption, Ripple Effect, Bullwhip Effect, Supplier Diversification, Digital Visibility, Global Supply Chain Pressure Index, Risk Mitigation*

I. INTRODUCTION

For three decades the dominant logic of global supply chain design was efficiency. Firms concentrated production where costs were lowest, reduced inventories through just-in-time replenishment, consolidated suppliers to obtain volume discounts and relied on long, finely tuned logistics networks. The result was a remarkable reduction in cost and a global value chain in which each country and firm specialised in a narrow task and did not produce the whole product. This system performed well under stable conditions, but it contained little slack, and its tight coupling meant that a disturbance in one place could propagate rapidly to many others [4], [7].

The COVID-19 pandemic demonstrated this vulnerability on a global scale. Factory closures, port restrictions, labour shortages and export controls interrupted flows of raw materials, components and finished goods at the same time that demand shifted abruptly between categories of products. Shortages of essential medical equipment, semiconductors and consumer goods followed, and delays and prices rose across the world [8], [9]. The scale of the shock can be seen in the Global Supply Chain Pressure Index (GSCPI), which combines transport costs and manufacturing survey indicators into a single measure expressed in standard deviations from its historical average [20]. As Fig. 1 shows, the index fluctuated within roughly one standard deviation of zero for most of the period from 2005 to 2019, with modest rises at the global financial crisis and at Brexit. It then rose sharply during the pandemic to above three standard deviations, and climbed further to more than four at the end of 2021 in what is widely described as the global supply chain crisis. A second rise followed the war in Ukraine in 2022.

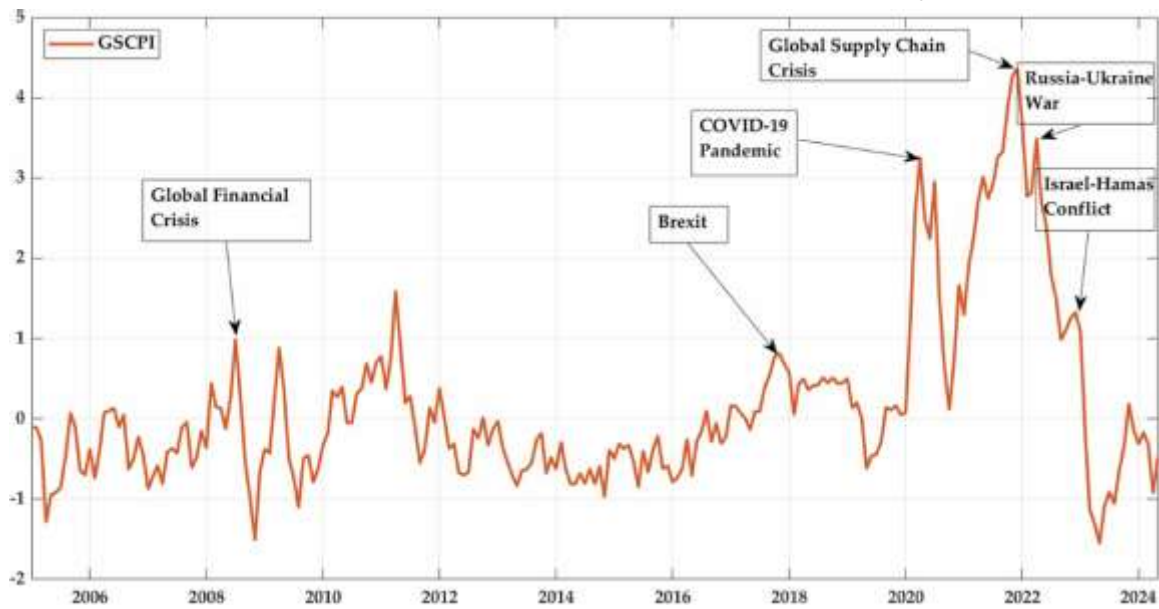


Figure 1: Global Supply Chain Pressure Index (GSCPI), 2005-2024, with major disruption episodes annotated

By 2023 the index had returned to and even below its long-run average, which might suggest that the crisis was over. That interpretation would be mistaken. Geopolitical rivalry, trade restrictions, climate-related events, cyber attacks and conflicts continue to threaten critical nodes and routes, and the post-pandemic environment is characterised by chronic uncertainty rather than a single recoverable shock. Industry analyses indicate that serious disruptions of a month or more should be expected to occur repeatedly over a decade and to erode a substantial part of annual profit over that period [19]. Boards and policymakers have therefore turned to resilience, but they face real trade-offs. Redundancy costs money; reshoring may reduce flexibility and raise costs; and visibility technologies require investment and data sharing. Firms lack consistent, quantified guidance on which measures to combine, in what proportion and with what expected return.

The objective of this research is to develop and evaluate an integrated framework for mitigating global supply chain disruptions in the post-pandemic era. The specific objectives are: (i) to structure the sources of disruption into a taxonomy that links each category to appropriate mitigation levers; (ii) to characterise the intensity and recurrence of disruption using the GSCPI; (iii) to define the Resilience in Motion framework with explicit practices and indicators; (iv) to formalise the framework mathematically so that decisions on inventory, sourcing and visibility can be quantified; and (v) to evaluate the framework by simulation against single-strategy alternatives in terms of fill rate, recovery time and total expected cost. The contribution of the paper is an evidence-based argument that resilience is a system property that arises from complementary measures, together with a method for assessing their combined value.

II. LITERATURE REVIEW

Research on supply chain disruption long predates the pandemic. Hendricks and Singhal showed that firms announcing supply chain disruptions suffered substantially lower long-run stock returns and higher equity risk than comparable firms, demonstrating that the financial consequences are large and persistent [10]. Chopra and Sodhi classified supply chain risks into categories such as disruptions, delays, forecast and inventory risks, and argued that every mitigation measure involves a trade-off, for example between the cost of holding inventory and the risk of shortage, so that strategies must be tailored to the risk [26]. Craighead et al. found that the severity of disruptions depends on design characteristics of the network, namely its density, complexity and the criticality of nodes, and on mitigation capabilities such as warning and recovery capability [11]. Tang catalogued robust strategies, including supply base flexibility, postponement, strategic stock and dynamic pricing, and Tang and

Tomlin showed that a limited amount of flexibility, such as having a small number of suppliers or limited process flexibility, can capture most of the benefit of full flexibility [27], [28].

Resilience as a concept has been defined in several ways. Christopher and Peck described resilience as the ability of a system to return to its original state or move to a new, more desirable state after being disturbed, and identified the redesign of the supply chain for resilience, collaboration, agility and a risk management culture as its main elements [12]. Sheffi emphasised that resilient enterprises combine redundancy and flexibility with a culture of continuous communication [13]. Ponomarov and Holcomb integrated the literature around the capabilities of readiness, response and recovery, and Kamalahmadi and Parast reviewed the principles of enterprise and supply chain resilience, stressing flexibility, redundancy, visibility and collaboration [14], [15]. Wieland and Durach distinguished resilience as the ability to recover from a disruption from resilience as the ability to sustain operations through it, a distinction that guides the structure of the present framework [16]. Quantitative treatments define the time to recover (TTR) and the time to survive (TTS) of each node, and they allow the identification of facilities whose failure threatens the network and of those with too much or too little redundancy [17].

The propagation of disruption through networks has been studied under the term ripple effect. Dolgui et al. reviewed the literature on the ripple effect, in which a local disruption spreads downstream and upstream through the network, and noted that its impact depends on network structure and on the timing of the disruption [21]. Ivanov and Dolgui extended the concept to intertwined supply networks and survivability, and later proposed digital supply chain twins to support the management of disruption risk [22], [23]. In the context of the pandemic, simulation by Ivanov showed that the impact of the outbreak depended strongly on the timing of facility closures and the duration of the closure relative to the time needed to restore production and transport [24]. Guan et al. estimated that the supply chain losses caused by control measures in one country spread through trade networks to many others, so that the total effect was much larger than the direct loss of output in the countries imposing the measures [8].

Fig. 2 summarises the sources of disruption considered in the literature on the pandemic. Four categories are distinguished: the direct effects of the outbreak itself on labour and production, including shortages of critical medical equipment [9]; policy-induced disruptions such as export restrictions and lockdowns [7], [25]; pandemic-induced behaviours, in which changes in customer and firm behaviour, such as panic buying and precautionary ordering, distort demand signals and trigger the bullwhip effect [1]; and disruptions induced by the supply chain strategy itself, such as single sourcing, offshoring and low inventory, which increase exposure to shocks [27]. This classification is useful because each category calls for different responses: capacity and workforce protection for direct effects, regulatory intelligence and geographic diversification for policy-induced effects, information sharing and rationing rules for behavioural effects, and structural redesign for strategic ones.

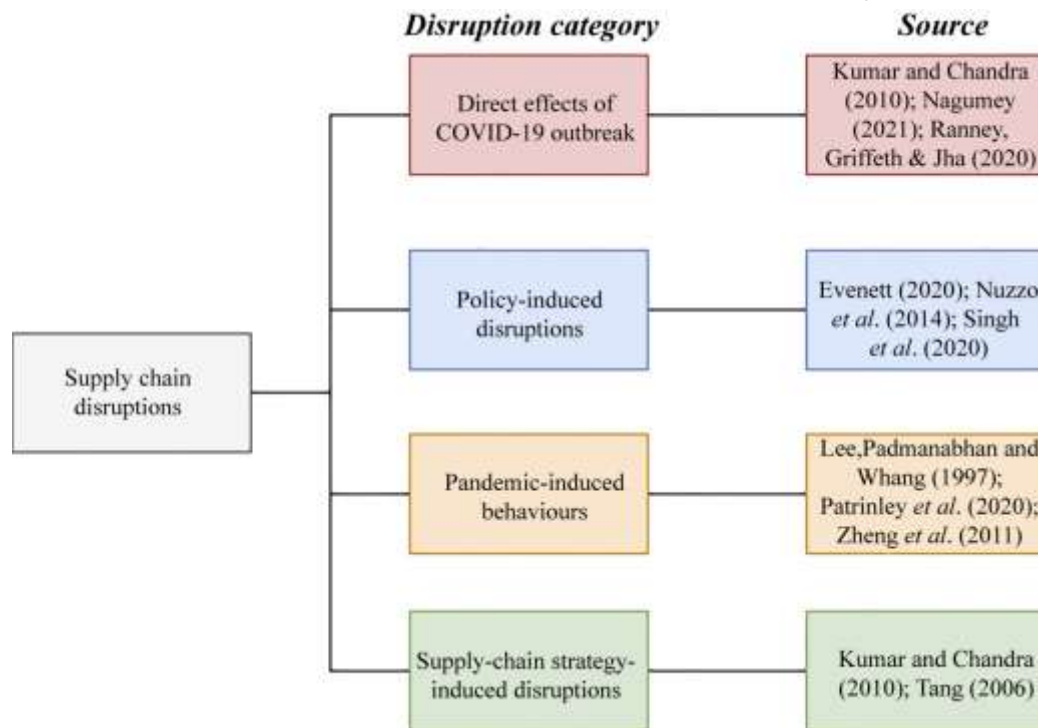


Figure 2: Taxonomy of supply chain disruption categories and their sources in the literature

Lee et al. identified four causes of the bullwhip effect, namely demand signal processing, rationing and shortage gaming, order batching and price fluctuations, and each of them was visible in the pandemic [1]. Understanding the mechanism matters because the amplification of orders upstream imposes costs on suppliers that are far from the final consumer and who have the least information.

III. RELATED WORK

Several recent studies have examined the effects of the pandemic on global value chains and the implications for strategy. Baldwin and Tomiura anticipated early in the crisis that trade would be affected not only through the direct disruption of production but also through the interdependence of supply chains [3]. Gereffi used the example of medical supplies to show how the pandemic exposed the vulnerability of global value chains and the difficulties of simply reshoring production, and he argued for a more nuanced approach involving diversification and regional capacity [6]. Baldwin and Freeman reviewed the evidence on risks in global supply chains and concluded that most disruption comes from shocks that hit domestic as well as foreign suppliers and that diversification across countries does not by itself protect against global demand or supply shocks, so that the case for wholesale reshoring is weak [4]. Queiroz et al. mapped the research agenda arising from the pandemic and identified digital technologies, resilience and sustainability as central themes [18].

On the quantitative side, Ivanov applied simulation to assess the impact of an epidemic outbreak on a global supply chain and found that the outcome depended on the timing and duration of disruptions at different tiers [24]. Hosseini et al. reviewed quantitative methods for resilience analysis, including optimisation, simulation and network analysis, and called for models that integrate several strategies rather than analysing each in isolation [29]. Pettit et al. proposed a capability and vulnerability assessment tool for supply chain resilience [30]. Simchi-Levi et al. advocated stress tests and the analysis of time-to-recover and time-to-survive to identify and prioritise risk mitigation investments [17].

These contributions leave three gaps. First, studies tend to analyse a single mitigation lever, such as inventory, sourcing or reshoring, and give less attention to their interaction. Second, taxonomies of disruption are seldom

linked explicitly to scenario design and to the choice of mitigation measures. Third, few studies combine a macro-level indicator of supply chain pressure with a network-level evaluation of strategies. The present paper addresses these gaps by using the GSCPI to characterise the environment, a four-category taxonomy to design scenarios, and a common simulation to compare single and integrated strategies.

IV. METHODOLOGY

Research Design

The study uses a three-part design. First, the macro environment is characterised through an analysis of the GSCPI shown in Fig. 1, which provides a standardised measure of global supply chain pressure. Second, the Resilience in Motion framework is specified, with practices and indicators for each stage and a mapping to the four disruption categories of Fig. 2. Third, the framework is evaluated by simulation on a multi-tier global network, where it is compared with alternative single-lever strategies under scenarios that represent each disruption category. This design combines a descriptive analysis of the environment with a controlled comparison of strategies, which makes it possible to attribute differences in performance to the strategy and not to the scenario.

Characterising Disruption Intensity

The GSCPI is expressed in standard deviations from its average. A month t is classified as one of elevated pressure when the index G_t exceeds a threshold θ , taken as one standard deviation. The severity of an episode is measured by the cumulative excess pressure over its duration, and the expected annual loss from disruption is the product of the frequency, duration and unit cost of disruption:

$$S = \sum_t \max(0, G_t - \theta), \quad E[L] = \sum_i p_i \cdot T_i \cdot c_i \quad (1)$$

where p_i is the annual probability of a scenario i , T_i the weeks of lost throughput and c_i the loss per week. Table 2 later reports the episodes read from Fig. 1. These quantities link the macro environment to the parameters used in the simulation.

The Resilience in Motion Framework

The framework contains five stages arranged as a continuous cycle, because resilience is built, tested and refined over time rather than achieved once. Sense detects early signs of disruption through monitoring of suppliers, logistics, geopolitical events, GSCPI-type indicators and demand signals. Absorb provides the buffers that sustain service during the disruption: strategic inventory for critical items, spare capacity and financial reserves. Adapt reconfigures sourcing, production and logistics during the disruption through supplier diversification, flexible capacity, alternative routes and, where justified, regionalisation. Recover restores normal performance quickly through pre-agreed recovery plans, prioritised restart of critical nodes and collaborative commitments with partners. Learn captures knowledge from every event and from stress tests, and it feeds improvements back into design. Table 1 specifies the objectives, practices and indicators of each stage and shows the categories of disruption they address.

TABLE 1. The Resilience in Motion Framework

Stage	Objective	Core practices	Indicators	Main disruption categories addressed
Sense	Early detection	Multi-tier mapping, control tower, event monitoring, demand sensing	Lead time to alert, % of spend mapped to tier 3	Policy, behaviour
Absorb	Sustain service	Strategic stock for critical items, capacity reserves, safety stock sized for lead-time variability	Weeks of cover, minimum fill rate	Direct, behaviour

Adapt	Reconfigure	Dual sourcing, flexible contracts, multi-region capacity, alternative routing	Effective supplier count, switching time	Policy, strategy
Recover	Restore performance	Recovery playbooks, prioritised restart, partner collaboration	Time to recover (TTR), cost of recovery	Direct, strategy
Learn	Improve continuously	Post-event reviews, stress tests, scenario planning, digital twin	Actions closed, stress-test coverage	All

Mathematical Models

Absorb. Inventory buffers must be sized for variability in both demand and lead time, and the pandemic showed that the second component dominates. With service factor z , mean lead time L , lead-time standard deviation σ_L , mean demand per period $\bar{d}$ and demand standard deviation σ_d , the safety stock is

$$SS = z \cdot \sqrt{L\sigma_d^2 + \bar{d}^2\sigma_L^2} \quad (2)$$

Adapt. The concentration of the supply base is measured by the Herfindahl-Hirschman index of supplier shares s_j , and its reciprocal is the effective number of suppliers:

$$HHI = \sum_j s_j^2, N_{\text{eff}} = \frac{1}{HHI} \quad (3)$$

A single-sourced component has $HHI = 1$ and $N_{\text{eff}} = 1$, and the best achievable value with N equally weighted suppliers is $N_{\text{eff}} = N$. Even limited flexibility captures a large part of the available benefit, as Tang and Tomlin showed [28], which suggests that two or three well-chosen suppliers can be sufficient for most items.

Sense and behaviour. Amplification of demand variability is measured by the bullwhip ratio of the variance of orders placed on the supplier to the variance of demand received from customers [1]:

$$BW = \frac{\text{Var}(\text{orders})}{\text{Var}(\text{demand})} \quad (4)$$

Values above 1 indicate amplification. In the pandemic, panic buying, shortage gaming and order batching increased this ratio, and information sharing and rationing based on historical sales reduce it.

Ripple effect. The way a shutdown spreads through the network is illustrated in Fig. 3. When factories in the pandemic-affected country shut down to stop the virus, they stop producing and also stop importing inputs, so that partner countries cannot sell parts and components along the chain, reduce their own output and buy fewer inputs from abroad. In the last stage, even countries with working production and no direct dependency on the affected country see exports fall through contagion. This chain reaction is represented by a propagation model on the network. Let $l_j(t) \in [0, 1]$ be the fraction of output of node j lost at time t , a_{ij} the share of node j 's critical input obtained from node i , and $b_j \in [0, 1]$ the proportion of the loss absorbed by node j 's buffers and alternative sources. Then

$$l_j(t+1) = \min \left(1, (1 - b_j) \cdot \sum_i a_{ij} \cdot l_i(t) \right) \quad (5)$$

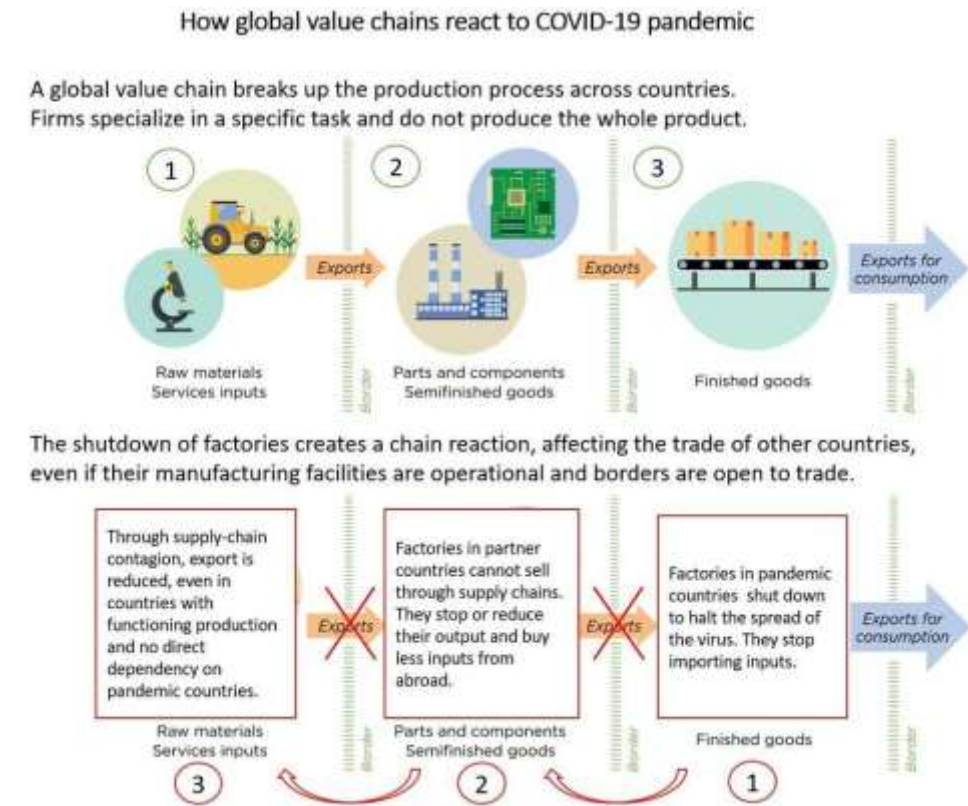


Figure 3: How global value chains react to the COVID-19 pandemic: shutdowns propagate through the chain

Equation (5) shows how resilience measures reduce propagation: dual sourcing lowers each a_{ij} of the failed supplier, while inventory and flexible capacity raise b_j . A shutdown at an upstream node therefore decays as it moves through well-protected nodes and amplifies through unprotected ones.

Recovery and overall resilience. Following Simchi-Levi et al., the time to recover (TTR) of a node is the time required for it to return to normal operation after a disruption, and the time to survive (TTS) is the time for which the network can match supply with demand using its buffers and alternative sources before performance falls [17]. In this study, performance is measured by the fill rate $F(t)$, the fraction of customer demand met at week t , and TTR is the time from the onset of the disruption until $F(t)$ first reaches 95%. Overall performance is summarised in a composite resilience score formed from normalised indicators s_k with weights w_k :

$$R = \sum_k w_k \cdot s_k, \quad s_k \in [0, 1], \quad \sum_k w_k = 1 \quad (6)$$

with indicators for minimum fill rate, speed of recovery (inverse of TTR), service-weighted cost efficiency and supplier diversity. The weights are 0.35, 0.30, 0.20 and 0.15 respectively, in line with the priority that managers give to continuity of service. Finally, the total expected cost of a strategy is the steady-state supply chain cost, which includes the extra cost of holding the strategy in place, plus the expected disruption loss $E[L]$ of Eq. (1).

V. EXPERIMENTAL SETUP

Macro Environment: GSCPI Episodes

Table 2 summarises the major episodes visible in Fig. 1 using approximate peak readings. The pandemic peak of about 3.3 standard deviations was more than three times the reading at the global financial crisis, and the peak of the global supply chain crisis at the end of 2021, at more than 4.3, was over four times that level. The index stayed above one standard deviation for most of the period from spring 2020 until early 2023, which is a duration of roughly three years, interrupted by short relapses. By contrast, the global financial crisis and Brexit produced short and moderate rises. The index then fell below -1.5 in early 2023 and remained near zero through 2024. Two features of this record shape the design of the evaluation: disruptions can be both severe and long, and their sources differ from one episode to the next, which supports the use of scenarios that represent different categories rather than a single stylised shock.

TABLE 2. Major Disruption Episodes Read from the GSCPI (approximate peaks)

Episode	Approximate peak (std. dev.)	Multiple of global financial crisis peak	Character
Global financial crisis (2008)	1.0	1.0	Demand collapse, credit shock
Brexit (2017)	0.8	0.8	Policy uncertainty
COVID-19 pandemic (spring 2020)	3.3	3.3	Direct effects and lockdown policy
Global supply chain crisis (end of 2021)	4.3	4.3	Demand surge, congestion, shortages
Russia-Ukraine war (2022)	3.5	3.5	Geopolitical, energy and commodity shock
Israel-Hamas conflict (annotated episode)	1.3	1.3	Regional conflict, shipping risk

Simulated Network and Scenarios

The evaluation uses a discrete-time, weekly simulation of a four-tier network with 60 nodes: 12 raw-material suppliers, 20 component manufacturers, 16 assembly plants and 12 distribution centres, located in three regions (Asia, Europe and North America). Mean demand is 1,000 units per week at each distribution centre with a coefficient of variation of 12%, replenishment follows an order-up-to policy, and the horizon is 52 weeks. Disruption propagates according to Eq. (5). Each configuration was run 500 times with random seeds, and results are means. In the baseline, which represents lean practice before the pandemic, critical components have a single supplier ($\text{HHI} = 0.62$, $N_{\text{eff}} = 1.6$), inventory cover is 1.5 weeks and 80% of component capacity is located in one region.

Four scenarios were designed, one for each category of the taxonomy in Fig. 2 (Table 3). The scenarios were calibrated to match the order of magnitude of the pandemic-era episodes in Table 2 rather than to reproduce any single event. As an illustration of why inventory must be sized for lead-time variability, consider a component with mean demand of 1,000 units per week, demand standard deviation of 120, mean lead time of 4 weeks and a 95% service factor ($z = 1.65$). With a lead-time standard deviation of 0.5 weeks, Eq. (2) gives a safety stock of about 915 units; when the lead-time standard deviation rises to 2 weeks, as it did for many lanes during the pandemic, the requirement rises to about 3,320 units, a 3.6-fold increase. This is the reason that the Absorb stage in the framework is sized on lead-time variability and not on demand variability alone.

TABLE 3. Disruption Scenarios

Scenario	Category (Fig. 2)	Description	Duration
S1 Shutdown cascade	Direct effects	Closure of 35% of component capacity in the main region, then a 4-week restart; propagates by Eq. (5)	8 weeks + 4 restart
S2 Export restriction	Policy-induced	Cross-border flows out of one region cut by 60%	12 weeks

S3 Demand panic	Behaviour-induced	Demand rises 40%; customers over-order by 1.5 times and orders are batched	6 weeks
S4 Sole-supplier failure	Strategy-induced	Failure of the single supplier of a critical component	10 weeks

Strategies Compared

Six configurations were compared (Table 4). Buffer inventory adds cover for critical items only. Dual sourcing qualifies additional suppliers for critical components. Regionalisation relocates 40% of component capacity to the region of demand at a cost premium of 12% on the relocated share. Digital visibility provides multi-tier mapping and a control tower, which gives alerts three weeks earlier and reduces order amplification through information sharing. The integrated framework applies the five stages together, with moderate levels of each lever: four weeks of cover on critical items, $N_{eff} = 4.2$ ($HHI = 0.24$), 25% of capacity regionalised, visibility, a pre-agreed recovery playbook and quarterly stress tests.

TABLE 4. Strategy Configurations

Strategy	Inventory cover (weeks)	Supplier concentration (HHI)	Regionalised capacity (%)	Visibility
Baseline (lean)	1.5	0.62	0	No
Buffer inventory	5.5	0.62	0	No
Dual sourcing	1.5	0.42	0	No
Regionalisation	1.5	0.62	40	No
Digital visibility	1.5	0.62	0	Yes
Integrated framework	4.0	0.24	25	Yes

The metrics are the minimum weekly fill rate, the time to recover to 95% fill rate (TTR), the bullwhip ratio of Eq. (4), the composite resilience score of Eq. (6) and the total expected cost, defined as the steady-state supply chain cost plus the expected disruption loss, both indexed to 100 for the baseline.

VI. RESULTS

Performance in the Shutdown Cascade

Table 5 and Fig. 4 show the results for scenario S1, the closest analogue of the pandemic shutdown illustrated in Fig. 3. The lean baseline was the most exposed: the fill rate fell to 41% and the network needed 26 weeks to recover to 95%. Each single strategy improved performance, but in different ways. Buffer inventory and dual sourcing raised the minimum fill rate to 63% and 68%, because they strengthen the node-level absorption parameter b_j and reduce the dependency shares a_{ij} in Eq. (5). Regionalisation reached 66% and the shortest recovery among the structural measures (14 weeks), since regional capacity was not affected by the cross-border cascade. Digital visibility did the least for the depth of the fall (59%) but it shortened recovery to 12 weeks, because earlier alerts and shared information accelerated re-planning. The integrated framework combined these effects: the fall was limited to 86%, and the network recovered in 7 weeks, which is roughly a quarter of the baseline recovery time. The composite resilience score rose from 0.31 for the baseline to 0.88 for the integrated framework, whereas single strategies scored between 0.46 and 0.55.

TABLE 5. Results for Scenario S1 (Shutdown Cascade), mean of 500 runs

Strategy	Minimum fill rate (%)	TTR (weeks)	Bullwhip ratio	Resilience score R
Baseline (lean)	41	26	3.4	0.31
Buffer inventory	63	19	3.0	0.46
Dual sourcing	68	15	3.1	0.55
Regionalisation	66	14	3.0	0.50
Digital visibility	59	12	1.9	0.49
Integrated framework	86	7	1.6	0.88

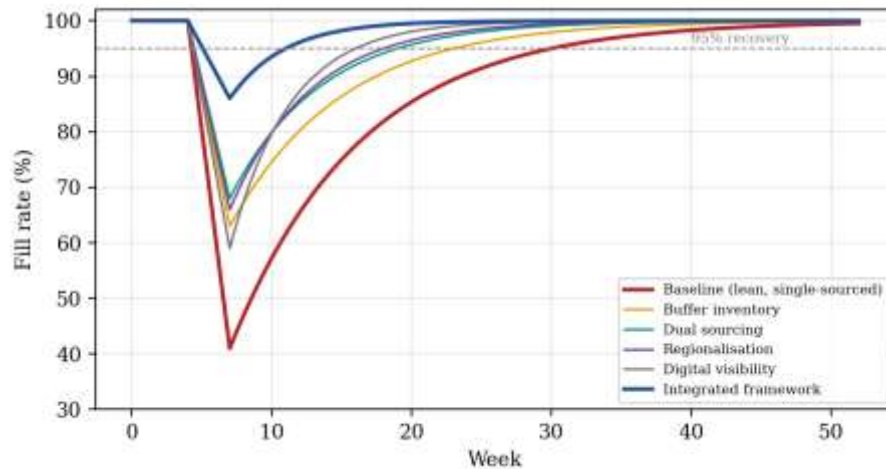


Figure 4: Fill-rate trajectories after a disruption at week 4 under each strategy (scenario S1)

Results Across the Four Disruption Categories

Table 6 compares the baseline and the integrated framework in all four scenarios. The framework improved the minimum fill rate and the recovery time in each category, with the largest gain in the strategy-induced scenario S4, where the failure of a single supplier cut the baseline fill rate to 36% and required 30 weeks to recover, compared with 82% and 9 weeks under the framework. In the behavioural scenario S3, the improvement came mainly from the information-related levers: the bullwhip ratio fell from 3.4 to 1.6 as order amplification was reduced by information sharing and rationing rules. Averaged over the four scenarios, TTR fell from 23.5 to 6.8 weeks. The pattern supports the taxonomy-based design: no single lever dominated across categories, and the integrated framework was robust because it contained a lever matched to each type of disruption.

TABLE 6. Baseline versus Integrated Framework by Scenario

Scenario	Min. fill rate: baseline (%)	Min. fill rate: framework (%)	TTR: baseline (weeks)	TTR: framework (weeks)
S1 Shutdown cascade	41	86	26	7
S2 Export restriction	52	88	21	6
S3 Demand panic	58	91	17	5
S4 Sole-supplier failure	36	82	30	9
Mean	46.8	86.8	23.5	6.8

Sensitivity tests examined the effect of longer disruptions. When the duration of S1 was doubled, the baseline minimum fill rate fell from 41% to 27% and its recovery time rose to 41 weeks, while the integrated framework fell from 86% to 74% and recovered in 12 weeks. This asymmetry, a loss of 14 points against 12, is small in absolute terms, but the baseline entered a regime in which recovery of service took close to a year. The supplier concentration index also proved influential: raising the framework's HHI from 0.24 to 0.42 lowered the minimum fill rate in S4 by nine points, which shows that effective diversification matters more than the mere existence of a second supplier.

Cost and Expected Value

Resilience has a price. Table 7 shows that holding extra inventory raised the steady-state cost index by 9.8%, dual sourcing by 6.4%, regionalisation by 11.2%, visibility by 3.1% and the integrated framework by 8.9%. Expected disruption loss, computed from Eq. (1) with scenario probabilities calibrated to the frequency of the episodes in Table 2, was 20 index points for the baseline and fell by 32% with buffers, 40% with dual sourcing, 38% with regionalisation, 20% with visibility and 62% with the integrated framework. Adding the two components gives a total expected cost of 101.4 for buffer inventory, 97.1 for dual sourcing, 101.4 for

regionalisation, 98.5 for visibility and 94.7 for the integrated framework. Two of the single strategies therefore cost more than the baseline in expected terms, and the integrated framework is the cheapest option, with a reduction of 5.3%. The explanation is that the levers are complementary: the information provided by visibility lowers the amount of inventory that is needed, diversification reduces the exposure that inventory must cover, and a recovery playbook shortens the period for which either must be used. Because the loss distribution is skewed, the benefit would be larger still for a risk-averse firm that values avoiding the worst outcomes.

TABLE 7. Total Expected Cost (baseline = 100)

Strategy	Steady-state cost	Expected disruption loss	Total expected cost	Change vs baseline (%)
Baseline (lean)	80.0	20.0	100.0	0.0
Buffer inventory	87.8	13.6	101.4	+1.4
Dual sourcing	85.1	12.0	97.1	-2.9
Regionalisation	89.0	12.4	101.4	+1.4
Digital visibility	82.5	16.0	98.5	-1.5
Integrated framework	87.1	7.6	94.7	-5.3

VII. DISCUSSION

The results support three conclusions. First, the lean configuration that was optimal under stable conditions is highly fragile under disruption, and the fragility is concentrated in a few structural features: single sourcing, minimal buffers and geographic concentration. Each is a rational choice in isolation and a vulnerability in combination, which echoes the observation that the design characteristics of a network, such as density and node criticality, determine the severity of disruptions [11]. Second, resilience measures are complements. Buffers deal with depth, diversification and regionalisation with duration, and visibility with the speed of response, so that the combination outperforms any one of them and, in expected-cost terms, outperforms them by a margin that is larger than the differences among them. This agrees with the view that firms should hold a portfolio of capabilities rather than a single remedy [5], [26]. Third, the benefit is not in the average year but in the tail, which is why the case for resilience is often rejected on a calculation that ignores the probability and the cost of rare events. The history of the GSCPI in Fig. 1 suggests that such events recur and that their intensity can far exceed the previous maximum.

The findings also have implications for the debate on reshoring. Regionalisation was effective in the shutdown scenario, but it was the costliest lever and it did not outperform dual sourcing on total expected cost. A moderate degree of regional capacity within a diversified portfolio performed better than a large one, consistent with the position that wholesale reshoring is not a general solution [4], [6]. Managers should instead identify critical items with high impact and long recovery time, using TTR and TTS analysis [2], [17], and concentrate redundancy where the expected loss is greatest. For policymakers the results indicate that incentives for firms to share information and to map multi-tier suppliers can have a large effect on systemic resilience at a comparatively low cost.

There are limitations. The simulation is stylised, with a single product family, an order-up-to policy and scenarios calibrated to magnitudes rather than to a specific firm; real networks are larger and contain information asymmetries and contractual constraints that are not modelled. The cost parameters are assumptions, and the probabilities of disruption are subjective. The GSCPI is an aggregate indicator and does not describe conditions in individual industries. Finally, the framework's learning stage and the organisational factors that determine whether practices are actually adopted were represented only through their effect on parameters. The estimates should be regarded as indications of the relative value of strategies, not as forecasts.

VIII. CONCLUSION

This paper presented Resilience in Motion, a five-stage framework of Sense, Absorb, Adapt, Recover and Learn for mitigating global supply chain disruptions in the post-pandemic era, and evaluated it against single-lever strategies in a simulated global network. An analysis of the Global Supply Chain Pressure Index showed that pandemic-era pressure was several times that of earlier crises, and a taxonomy of four disruption categories guided the design of the scenarios. In the shutdown cascade the framework limited the fall in fill rate to 86%, compared with 41% for the lean baseline, and recovered in 7 weeks instead of 26. Across all four categories the mean recovery time fell from 23.5 to 6.8 weeks, and total expected cost fell by 5.3% even though steady-state cost rose by 8.9%. Two of the four single strategies cost more than the baseline in expected terms, which shows that resilience investments should be designed as portfolios whose levers reinforce one another. Future research should test the framework with firm-level data, extend the model to multiple products and to financial constraints, and examine how digital twins and artificial intelligence can strengthen the Sense and Learn stages.

IX. REFERENCES

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