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Operational Resilience Anew

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PRELIMINARY DRAFT - PLEASE DO NOT CIRCULATE

Unexpected and significant disruptions in the global supply chain may require swift and substantial adjustments to corporate physical operations, such as downsizing or reshoring. We conjecture that integrated risk management (IRM), incorporating *appropriate* financial hedging, can mitigate the extent of these adjustments, thereby strengthening operational resilience. Our approach is normative. Using an unreliable supply newsvendor model, we identify, develop, and evaluate classes of such hedges by analytically deriving and comparing the optimal standalone operational policies with the optimal IRM policies. Our theoretical findings reveal four major features: i) *Financially-driven operational expansion*: The optimal size of operations increases with the use of hedging and with greater hedge complexity. ii) *Disruption-driven operational contraction*: When supply reliability decreases, firms should scale down their operations; iii) *Demand-driven operational fragility*: Conventional IRM strategies centered on demand hedging may intensify the operational adjustments necessitated by a disruptive event, thereby weakening operational resilience. iv) *Financially-driven operational resilience*: Optimal IRM policies incorporating supply risk hedging significantly mitigate disruption-driven operational reductions compared to purely operational approaches, thereby enhancing operational resilience. We extend and empirically validate these findings using a novel multinational capacity allocation model. This model is applied to a representative European gas firm managing the balance between Russian natural gas and U.S. LNG procurement following the supply chain disruptions caused by the Russo-Ukrainian war and the sabotage of the Nord Stream pipelines. Our analysis demonstrates that optimal IRM policies incorporating gas supply risk hedging (or even cross-hedging) could have mitigated the reshoring requirements prompted by these events.

Key words: Financial Hedge Design, Integrated Financial-Operational Risk Management (IRM), Interfaces of Finance, Operations, and Risk Management (iFORM).

1. Introduction

Extreme events, such as pandemics, geopolitical crises, and natural catastrophes, can result in sudden disruptions of firms' supply chains (Birge et al. (2023)). This phenomenon often necessitates undertaking prompt and significant changes in physical operations, primarily involving updates in quantity ordering and capacity relocation. For example, in 2022 Apple announced plans to partially reshore their production to Vietnam amid escalating geopolitical tensions between China and the United States, as well as recurrent supply disruptions stemming from China's zero-COVID policies (Ting-Fang (2022)). Similarly, BP and Shell have disclosed their intentions to divest from all Russian oil and gas projects following the Russo-Ukrainian war outbreak (Bousso (2022)).

It turns out that only a few actors actually execute these operational changes, while some cannot do so even though they recognize the need. For instance, Capgemini (2022) highlights that 92% of a representative pool of interviewed firms are fully aware of their relocation needs, yet only 15% declare themselves appropriately equipped to handle the related processes. More broadly, Cohen et al. (2018) reveal that sourcing decisions might be unresponsive to the latest events. The primary reason for this inertia lies in the burden of these actions in terms of temporal, physical, and financial resources required for their execution. In this context, a major role is played by supply chain (SC) resilience, defined as firms' ability to recover from a temporary change and "*to proactively plan for adapting ... to 'new normal' conditions and risks, and preparing it to effectively mitigate future shocks of an unknown nature*" (Cohen and Kouvelis (2021)).

While existing practices and academic research emphasize the use of operational tools to ensure and support resilience (Lücker et al. (2024)), we focus instead on leveraging financial flexibility. Specifically, we propose a novel method to mitigate the effects of sudden SC disruptions on physical operations. Our approach centers on the adoption of appropriate financial hedges within an integrated risk management (IRM) framework and seeks to explore whether, and to what extent, this strategy can enhance operational resilience. A positive outcome from this inquiry could significantly contribute to addressing the managerial challenge of identifying and developing cost-effective, flexible, and efficient strategies to mitigate SC disruptions. Furthermore, it would provide international policymakers with a new approach to implement actions that fortify the global SC, particularly in the context of geopolitical tensions.

1.1. Research Question and Key Findings

Historical observations of SC disruptions highlight two important phenomena. First, such disruptions are occurring with increasing frequency (World Economic Forum (2021)). Second, their transitory or permanent nature is difficult to determine upfront and may turn out to be mixed (Simchi-Levi et al. (2014)). A quintessential example is the Covid-19 pandemic: while some disruptions were temporary and companies adapted, the pandemic has led to lasting changes in how supply chains are managed and structured (Knut et al. (2021)).

We argue that an effective way to manage corporate risks in such a context is to mitigate the immediate impact of disruptions on operations. If the disruption proves temporary, the firm can more easily revert to its original configuration. Conversely, if it turns out to be permanent, the firm can allocate the savings from a reduced impact toward additional time and resources to facilitate further adjustments. In either case, mitigating operational shifts strengthens the firm's operational resilience. Our study demonstrates that appropriate financial hedging mitigates the operational shift required by optimal operational handling, thereby bolstering operational resilience. This intuition can be elucidated by outlining the logical pathway of our approach.

Consider a firm operating in a market under a normal regime, where the SC functions ordinarily. Let their business revenues be adjustable through an operational variable, say a procurement, a production, or a capacity allocation order. They maximize a decision criterion and select the *optimal naked operational level under normalcy*, where the term "naked" emphasizes the absence of any hedge. Suppose an unexpected event occurs, leading to a transition to a disrupted regime featuring unreliable supply. The firm must now adjust its operations to a new level, referred to as the *optimal naked operational level under disruption*. In general, operations may either expand or contract. The absolute variation in the optimal naked operational level resulting from the regime switch, with no hedging in place, defines the *naked operational shift* that follows an SC disruption. This shift represents the firm's operational effort required to maintain optimal decision-making.

When a firm is risk-averse (or risk-constrained), overall revenues can benefit from financial hedging (Ding et al. (2007)). Instead of selecting an operational level alone, the firm chooses a combination of this level with a financial hedge—an IRM policy—to maximize a risk-adjusted (or risk-constrained) decision criterion. This results in two IRM policies that establish the *optimal hedged operational level* either *under normalcy* or *under disruption*. The absolute change in this

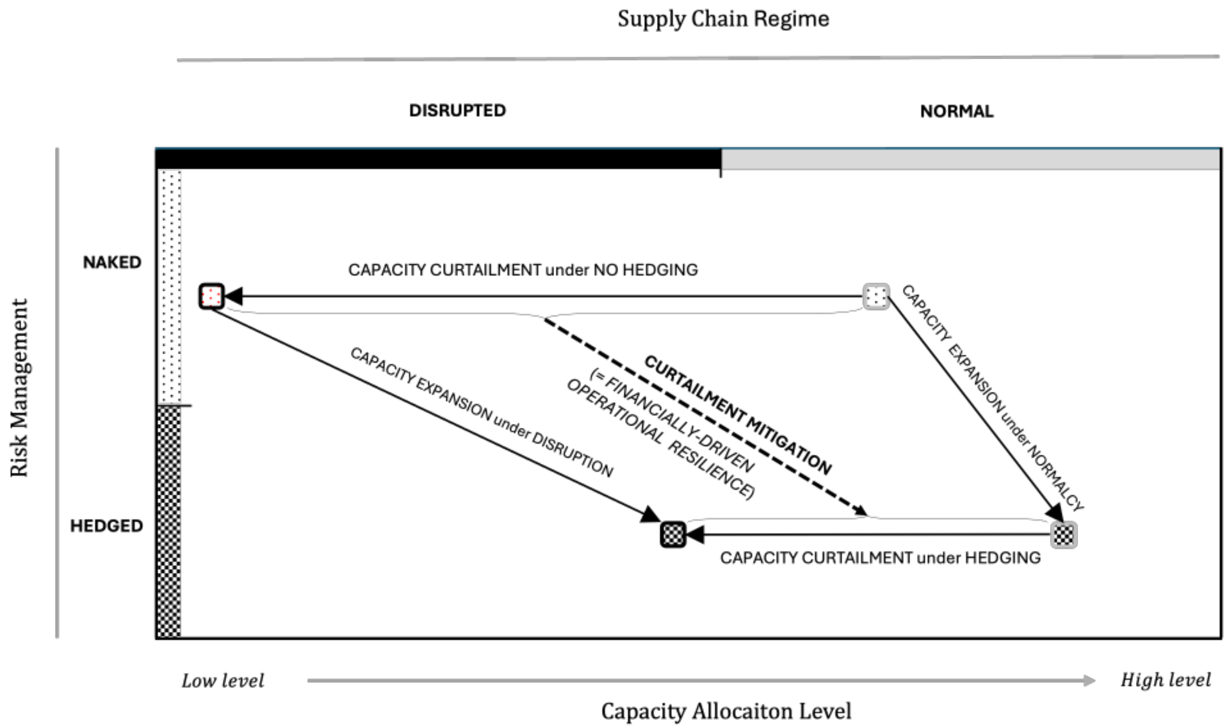


Figure 1 The logical pattern of financially-driven operational resilience enhancement.

level when transitioning from normal to a disrupted regime, with a hedge in place, defines the *hedged operational shift* that follows an SC disruption.

Our main research question is whether and how a firm can leverage financial hedging to mitigate disruption-driven operational shifts, thereby enhancing resilience. Figure 1.1 illustrates this point in the context of capacity planning. It is well established that appropriate financial hedging increases capacity allocation relative to the no-hedging case under normalcy (rightmost right-downward arrow indicating capacity expansion) (Ding et al. (2007)). We confirm this result and extend it, showing: i) *Financially driven operational expansion under disruption*: Optimal capacity allocation grows with hedging *and* with increasing hedge complexity under disruption as well (leftmost right-downward arrow indicating capacity expansion); ii) *Disruption-driven operational contraction*: Supply chain disruption reduces capacity allocation both under pure operational handling and under IRM (leftward arrows showing capacity curtailment); iii) *Demand-driven operational fragility*: Conventional demand hedging may exacerbate capacity curtailment, weakening operational resilience (*i.e.*, increasing fragility). iv) *Financially driven operational resilience*: Suitable financial hedging mitigates the degree of capacity curtailment *vs.* operational handling alone (right-downward dashed arrow showing curtailment mitigation), thus enhancing operational resilience.

1.2. Literature Review and Contribution

We examine the effect of supply chain disruptions on optimal physical operations and identify financial tradables that mitigate this impact, thereby enhancing operational resilience. Thus, our study aims to contribute to the literature on disruption risk and IRM, bridging these two streams. This positions our research agenda at the interface of finance and operations (Babich and Kouvelis (2018), Wang et al. (2021)).

Disruption risk is traditionally associated with exposure to supply uncertainty, often modeled using random production yield and/or capacity (Wang and Gerchak (1996)). The operations management (OM) literature has extensively analyzed the impact of disruption risk on physical operations and developed operational strategies to mitigate this impact, such as supplier diversification, inventory management, or emergency supply, thereby enhancing operational resilience (*e.g.*, Tang and Kouvelis (2011); Ang et al. (2017); Jain et al. (2022); Birge et al. (2023); Chen (2024)).

The use of non-operational tools, such as insurance contracts or financial claims, to address supply disruption risk—potentially alongside operational measures—remains uncommon. Some authors focus on non-tradable instruments. For instance, Babich (2010) propose the combined adoption of financial subsidies for supply (a non-operational tool) and capacity ordering (an operational tool) to mitigate disruption risk, while Dong and Tomlin (2012) advocate using business interruption insurance contracts (a non-operational tool) in conjunction with inventory management and emergency sourcing (operational tools) to manage supply risk. Our study advances the literature by examining IRM with tradable securities to enhance operational resilience.

First, we develop a NV model for capacity allocation model featuring unreliable supply and risk-averse preferences. This model differentiates between disruption and normal states through a quantification of supply reliability. For both the naked and IRM cases, we: (1) Derive generalized critical fractile equations and establish positive monotonicity of the optimal order quantity with respect to supply reliability, business profitability, and the firm's risk propensity; (2) Identify conditions under which hedging induces a counterbalancing expansion of operations as supply reliability decreases; and (3) Demonstrate that appropriate hedging enhances operational resilience to supply disruptions. In a similar NV model without parametric control over supply reliability, Tekin and Özekici (2015) show that risk aversion, with or without hedging, reduces the order quantity compared to the risk-neutral case, a conclusion that aligns with our findings.

Second, we expand our analysis to a capacity planning problem across two locations and propose a new capacity reshoring model incorporating supply risk within the framework of Ding et al. (2007). This model characterizes corporate behavior in allocating capacity before and after a disruptive event. We calibrate a model instance with real data to account for the European gas SC disruption following the Russo-Ukrainian war in 2022. Our analysis demonstrates IRM policies that could have mitigated the need for capacity relocation from Russian to U.S. supply sources. Interestingly, Zhao and Huchzermeier (2017) develop an IRM capacity planning model with random capacity and production decision making. Their study focuses on complementarity and substitution effects of IRM strategies, while we focus on identifying and quantifying resilience and fragility effects from SC disruptions. In this regard, our studies are complementary.

A unique aspect that distinguishes our model from all previously mentioned IRM-based studies is its clear differentiation between standard supply risk (*i.e.*, arising from routine business operations) and disruption risk (*i.e.*, resulting from exceptional events), as proposed by Kleindorfer and Saad (2005). Operational methods aimed at enhancing resilience are typically either disruption-targeted or dual-purpose (Lücker et al. (2024)). Following this approach, we define a standard supply shortage as any downward sample in random supply yield, while an SC disruption is represented by any shift in the supply yield distribution that decreases the supplier's reliability. Accordingly, disruption risk is classified as a form of model risk.

This distinction underpins our approach to achieving financially-driven operational resilience, which is the main contribution of this study. Since its inception in Ritchken and Tapiero (1986), IRM has focused on enhancing the risk-return trade-off for various business operations by counterbalancing adverse fluctuations in operating revenues with financial hedging payoffs (*e.g.*, Caldentey and Haugh (2006); Ding et al. (2007); Chod et al. (2010); Wang and Yao (2017)). All the aforementioned IRM models addressing supply risk adopt this model-endogenous approach, which is effective for managing business risk under normal conditions. However, when facing disruption risk, it is necessary to examine the impact of a drop in supply reliability (*i.e.*, an exogenous shift in a model parameter) on optimal operations with and without financial hedging. Operational resilience is achieved when hedging mitigates this impact differential on the level of optimal operations, as illustrated in Subsection 1.1. To our knowledge, this is the first study to propose a model risk approach to disruption risk using financial hedging within an IRM framework.

2. A Newsvendor Model with Unreliable Supply

In a single-sourcing context, supply chain (SC) disruptions may call for operational downsizing in terms of capacity, labor, and inventory. Enhancing operational resilience entails mitigating these downsizing requirements. We investigate this concept using an unreliable supply newsvendor model and develop analytic IRM strategies to bolster resilience against capacity downsizing demands.

2.1. Setup

Consider a one-period time frame $\{0,1\}$. Time 0 denotes the present moment, when all relevant information for decision-making is gathered; time 1 represents the point at which all uncertainty regarding the risk factors affecting operating revenues is resolved. This uncertainty is described by a probability space $(\Omega, \mathcal{F}, \mathbb{P})$, where Ω is the set of all possible future outcomes, $\mathcal{F}$ is the σ-algebra containing all events formed by these outcomes, and $\mathbb{P}$ is a probability measure reflecting the likelihood of these events, based on historical data, subjective beliefs, or a combination of both. Monetary values are expressed in U.S. dollars, and physical quantities are measured in "units". For simplicity, we assume the time value of money is negligible and therefore disregarded. This setup naturally suits one-stage decision problems. It also accommodates two-stage scenarios with a deterministic control problem in the second stage, such as when operating revenues are structured as real options, *e.g.*, newsvendor (Van Mieghem (1998)) and capacity planning (Ding et al. (2007)).

A firm faces random product demand $D \geqslant 0$ (1^{st} state variable) with a finite mean μ and variance σ^2 and distribution function F_D. Each ordered item costs $c > 0$ and, when received, it is sold at a price $p > c$. Product *onerousness* is measured by the cost-to-price ratio c/p and defines profitability through the critical fractile $1 - c/p$. The firm addresses demand by issuing an order quantity q, incurring a pay-per-order overall cost of cq dollars (Babich et al. (2007)) and receiving a random (*i.e.*, unreliable) supply of qY product units (Wang and Gerchak (1996)). Examples of such orders include capacity installment (Ding et al. (2007)) or a procurement order in a vertically integrated corporation that features production insourcing (Dada et al. (2007)).

We model unreliable supply using the all-or-nothing random proportional yield, whereby supply either succeeds or fails (Babich et al. (2007), Yang et al. (2009)). This property is represented by a (dimensionless) Bernoulli-distributed *yield factor* $Y \in \{0,1\}$ (2^{nd} state variable), which determines actual supply qY as either zero or the full order quantity q with probability $\rho \in [0,1]$. The corresponding supply function is a random map: order $q \to$ supply qY. The odds ρ quantify product *supply reliability* and define a standing *supply regime*. Any change in this parameter captures the effects of events that disrupt the underlying supply chain. Interestingly, the nature of such events is irrelevant for the definition of our model: whether caused by a global pandemic, geopolitical turmoil, or physical failure, the impact is represented through an exogenous drop in supply reliability. Note that the reliability odds ρ match the expected yield factor ($\mathbb{E}_{\mathbb{P}}[Y]$) under the assumed probability distribution. Last, we assume that product demand D and production yield Y are statistically independent (Dada et al. (2007), Kouvelis and Li (2019)).

Naked operating revenues result from meeting demand D up to the actual supply qY:

$$\pi_\rho(q) := p\min(D, qY) - cq. \tag{1}$$

Adding salvage or goodwill loss components would be immaterial to our results, as they would merely modify the critical fractile equations through their incorporation into underage or overage costs. The firm is risk-averse (Eeckhoudt et al. (1995)) and adopts mean-variance (MV) preferences, defined by a target criterion $\mathbb{MV}[\cdot] := \mathbb{E}[\cdot] - (a/2)\mathbb{V}[\cdot]$, where $\mathbb{E}$ and $\mathbb{V}$ denote the expectation and variance operators, respectively, and the coefficient a quantifies the firm's aversion to risk. The reciprocal risk aversion a^{-1} defines the firm's *risk propensity*. Appendix EC.2.1 provides regularity conditions that ensure the well-posedness of the optimization problems under investigation.

This completes the description of the Unreliable supply risk-averse NewsVendor (UNV) model, $\mathcal{M}(\rho, a)$, featuring supply reliability ρ and firm risk aversion a. Additional parameters defining a specific model instance (*i.e.*, a demand distribution F_D, a selling price p, and a unit cost c) are assumed to be provided. The UNV model generalizes both the standard (*i.e.*, reliable supply, $\rho = 1$, and risk-neutral, $a = 0$) and the reliable supply risk-averse NV models (Van Mieghem (2007)).

The optimal standalone (or pure, or naked) operational handling stems from maximizing the MV target of operating revenues $\pi_\rho(q)$ in a class Q of admissible order quantities, namely:

$$\mathcal{U}_0^* := \max_{q\in Q} \mathbb{MV}[\pi_\rho(q)] \to \arg\max =: q_0^*, \tag{2}$$

where the subscript "0" highlights the lack of hedging. Note that the optimal order quantity in principle depends on all model parameters, namely $q_0^* = q_0^*(\rho, a, c, p)$: when needed, we indicate its restriction to a parameter (or subset of parameters) # by $q_0^*(\#)$.

When following an IRM approach, the firm must identify a class $\mathcal{H}$ of financial contingent claims to trade in. We assume that each claim H is priced as V^H according to a valuation theory to specify upfront. Given a set $\mathcal{Q}\times\mathcal{H}$ of admissible integrated operational-financial policies and a dollar budget w to use for hedging purposes, the firm selects the IRM policy that maximizes the MV target of *hedged revenues* $\Pi_\rho(q,H) := \pi_\rho(q)+H$, namely:

$$\mathscr{U}^*_{\mathcal{Q}\times\mathcal{H}} := \max_{(q,H)\in\mathcal{Q}\times\mathcal{H}:\ V^H\leqslant w} \mathbb{MV}\left[\Pi_\rho(q,H)\right] \to \arg\max =: \left(q^*_{\mathcal{Q}\times\mathcal{H}}, H^*_{\mathcal{Q}\times\mathcal{H}}\right). \tag{3}$$

Henceforth, we omit indicating $\mathcal{Q}=[0,\infty)$ and denote the optimal IRM by $\left(q^*_{\mathcal{H}}, H^*_{\mathcal{H}}\right)$. Revenues $\Pi_\rho(q^*_{\mathcal{H}}, H^*_{\mathcal{H}})$ are the *optimal IRM revenues*. When the optimal order quantity $q^*_{\mathcal{H}}$ is strictly positive, we say that the business is *viable*. In addition, if the hedging class is a set $\mathcal{H}_Z$ of financial contingent claims written on an underlying index (or array of indices) Z, then the optimal IRM can simply be denoted as $\left(q^*_Z, H^*_Z\right)$ whenever the context is clear.

2.2. An Illustrative Example

The role of financial hedging in empowering operational resilience plastically emerges in a UNV model featuring predictable demand, wherein *all* derivations are analytic. Let the firm face supply risk only (Y random), while product demand is constant, say $D=d$. Assume that $q\geqslant 0$ is a capacity allocation (or, simply, capacity) leading to operating revenues $\pi_\rho(q) = p\min(d,qY)-cq$. These revenues entail a target:

$$\mathbb{MV}[\pi_\rho(q)] = \rho p\min(d,q) - cq - \frac{a}{2}\mathbb{V}[Y]\left(p\min(d,q)\right)^2 = \begin{cases} (\rho p-c)q - \frac{a}{2}\mathbb{V}[Y]q^2, & (q\leqslant d) \\ \rho p d - \frac{a}{2}\mathbb{V}[Y]d^2 - cq, & (q\geqslant d) \end{cases} \tag{4}$$

which proportionally decreases with increasing supply risk $\mathbb{V}[Y]$ and risk aversion a.

We can disentangle three supply regimes and as many optimal naked capacity allocations. If $\rho\leqslant c/p$, supply is unreliable, MV is decreasing in capacity q, and the optimal naked allocation prescribes to stay idle ($q^*_0=0$). If $c/p<\rho\leqslant c/p+(ad/p)\mathbb{V}[Y]$, supply is mildly reliable and MV exhibits a global maximum at $q^*_0=(\rho p-c)(a\mathbb{V}[Y])^{-1}$, a quantity comprised between the idle state 0 and full demand d. If $\rho>c/p+(ad/p)\mathbb{V}[Y]$, supply is highly reliable, MV is increasing in capacity q, and the optimal naked allocation matches product demand ($q^*_0=d$). The interval $(c/p,1]$ of reliability odds entailing a viable business ($q^*_0>0$) defines the *viable reliability region*.

Let supply yield forwards trade in a frictionless, arbitrage-free, and complete risk-neutral market. Then, the physical probability $\mathbb{P}$ serves as a pricing measure, and the forward supply yield is

Supply Regime	Operational Handling q_0^*	Integrated Risk Management (q_Y^*, θ_Y^*)
Unreliable $\rho \in [0, c/p]$	0	$(0, 0)$
Mildly reliable $\rho \in (c/p, c/p + (ad/p)\mathbb{V}[Y]]$	$(\rho p - c)(a\mathbb{V}[Y])^{-1}$	$(d, -pd)$
Highly reliable $\rho \in (c/p + (ad/p)\mathbb{V}[Y], 1]$	d	$(d, -pd)$

Table 1 Optimal operational handling and IRM across supply regimes.

the expected spot yield, $\mathbb{E}_{\mathbb{P}}[Y] = \rho$. When conducting IRM with supply yield forwards, the firm encounters the following instance of the optimization problem (3):

$$\max_{q \geqslant 0, \theta \in \mathbb{R}} \mathbb{MV}[\pi_\rho(q) + \theta(Y - \rho)] \longrightarrow \arg\max =: \left(q_Y^*, \theta_Y^*\right). \tag{5}$$

Clearly, zero budget constraint is implied by the very definition of forward price. Conditional to a capacity allocation q, the hedged revenues MV target attains a maximum value at the (short) forward holding:

$$\theta^*(q) = -p \min(d, q), \tag{6}$$

which noticeably is independent of supply reliability ρ. The optimal MV target reads as:

$$\mathbb{MV}[\pi_\rho(q) + \theta^*(q)(Y - \rho)] = \rho p \min(d, q) - cq = \begin{cases} (\rho p - c)q, \ 0 \leqslant q \leqslant d, \\ \rho p d - cq, \ \ q > d. \end{cases} \tag{7}$$

The message is clear: hedging supply risk fully removes the target loss brought over by the firm's aversion to supply risk; however, it cannot handle the depressive effect of unreliable supply on gross revenues via the $\rho p d$ term. The effect of financial hedging supply risk on capacity allocation emerges from analyzing the optimal conditional MV target (7). If supply is unreliable ($\rho \leqslant c/p$), this quantity decreases in capacity allocation q and attains a maximum at zero. The optimal IRM $\left(q_Y^*, \theta_Y^*\right) = (0, 0)$ requires the firm to drop out of the game. However, in the viable reliability region $(c/p, 1]$, target (7) increases in capacity allocation q and it attains a maximum at product demand d. The optimal IRM $\left(q_Y^*, \theta_Y^*\right) = (d, -pd)$ requires a short forward position with size matching the dollar value of operating gross revenues and demand is fully served. A comparison between optimal capacity allocations with and without hedging is offered in Table 1. IRM clearly makes optimal capacity allocation independent of risk aversion, of supply reliability, and of supply risk. In particular, for a mildly reliable supply, hedging shifts capacity allocation from $(\rho p - c)(a\mathbb{V}[Y])^{-1}$ to full demand d.

The effect of financial hedging supply risk on operational resilience in the aftermath of an SC disruption, say upon $(c/p <)\rho_1 \downarrow \rho_2$, results from comparing the curtailment of naked capacity $q_0^*(\rho_1) - q_0^*(\rho_2)$ and the curtailment of forward-hedging capacity $q_Y^*(\rho_1) - q_Y^*(\rho_2)$. The optimal naked capacity $q_0(\rho)$ vanishes over the interval $[0, c/p]$ and equals $(\rho p - c)/(a\rho(1-\rho))$ in the complementary region $(c/p, 1]$, where it is an increasing function of ρ. Consequently, the curtailment of optimal naked capacity is strictly positive provided the initial reliability exceeds the threshold c/p. Since the optimal forward hedged capacity $q_Y^*(\rho)$ is independent of supply reliability ρ, then the forward hedged capacity curtailment vanishes. Consequently, financial hedging mitigates (in this case, it annihilates) the capacity curtailment that follow a reliability drop. It thus enhances operational resilience. This shows our main result within the simplest nontrivial model setup.

2.3. Operational Handling

Consider the problem (2) of optimal operational handling in a UNV model $\mathcal{M}(\rho, a)$. A well-established result in OM states that the optimal quantity $q_{NV}^* := q_0^*(1)$ in a standard newsvendor model $\mathcal{M}(\rho = 1, a = 0)$ satisfies the *critical fractile equation*:

$$F_D(q) = 1 - \frac{c}{p}. \tag{8}$$

Focusing on symmetric demand distributions, Schweitzer and Cachon (2000) classify a product as *high profit* or *low profit* depending on whether the critical fractile exceeds or falls short of 1/2 or, equivalently, onerousness c/p is less than or greater than 1/2 . They also demonstrate that the optimal quantity is greater than the average demand for high-profit products and smaller for low-profit products. A similar argument can be extended to any UNV model. First, note that the designation of *high* or *low profit* can apply equally to a product, a business, or a production process. Therefore, we use these terms interchangeably. Additionally, we observe that expected revenues $\mathbb{E}[\pi_\rho(q)]$ increase with both profitability $1 - c/p$ and supply reliability ρ. Consequently, lower supply reliability requires higher profitability to maintain the same level of expected revenues. This relationship suggests that a product can be characterized by the balance between competing factors of reliability and profitability.

We classify a product (or a business, or a production process) as *high yield* or *low yield* based on whether its onerousness c/p is less than or greater than its supply reliability ρ. Intuitively, products with a reliable supply side (*i.e.*, a large ρ) can tolerate higher onerousness c/p, meaning lower profitability $1-c/p$, while still achieving a given level of expected profits. Interestingly, we can characterize the optimal order quantity q_0^* in terms of the supply regime ρ:

Proposition 1 (Optimal Quantity in a Naked UNV Model)**.** *The optimal order quantity q_0^* for a high-yield product ($c/p < \rho$) is the unique solution to the generalized critical fractile equation:*

$$F_D(q) = 1 - \frac{1}{\rho(1-ap\Psi_\rho(q))} \times \frac{c}{p}, \tag{9}$$

where:

$$\Psi_\rho(q) := (1-\rho)q + \rho \int_0^q F_D(x)\,dx. \tag{10}$$

The optimal order quantity for a low-yield product ($c/p > \rho$) is zero. In all cases, the optimal quantity is bounded above by the optimal quantity in the standard NV model $\mathcal{M}(1,0)$, i.e., $q_0^* \leqslant q_{NV}^*$, and they are equal if and only supply is fully reliable ($\rho = 1$) and the firm is risk neutral ($a = 0$).

This result indicates that any business involving a low-yield product is not viable. It also demonstrates that the lower the supply reliability ρ, the lower the cost-to-price threshold c/p required to achieve a positive order quantity. This theoretical result reflects an empirical observation: when an SC disruption decreases supply reliability, say $\rho_1 \downarrow \rho_2$, all products with profitability levels between ρ_2 and ρ_1 shift from high-yield to low-yield and are no longer ordered or produced ($q_0^* = 0$). The extent of this effect is closely tied to product profitability, with less profitable products (high onerousness) typically abandoned before highly profitable ones (low onerousness). Notably, the decision to cease production or procurement is independent of the firm's risk aversion a, whereas the optimal order size depends on all model parameters.

The generalized critical fractile equation (9) can be analytically solved in a few cases.

Example 1 (**Risk neutral firm**)**.** *Consider a risk-neutral firm ($a = 0$) facing unreliable supply ($\rho < 1$). Then, the optimal order quantity for a high-yield product ($c/p < \rho$) aligns with a standard newsvendor model featuring onerousness proportionally reduced onerousness by ρ^{-1}, i.e.,*

$$q_0^* = F_D^{-1}\left(1 - \rho^{-1} \times \frac{c}{p}\right). \tag{11}$$

If the product is low-yield, the optimal order quantity becomes zero, and the business remains idle.

Example 2 (**Risk averse firm and uniform demand**)**.** *Consider a risk-averse firm* ($a>0$) *facing unreliable supply* ($\rho<1$) *to meet a uniformly distributed* $\mathcal{U}[0,d]$ *product demand. Then, the optimal order quantity* q_0^* *for a high-yield product* ($c/p\leqslant\rho$) *satisfies a cubic equation:*

$$ap\frac{\rho}{2d^2}q^3-\frac{ap}{d}\left(1-\frac{\rho}{2}\right)q^2-\left(\frac{1}{d}+ap(1-\rho)\right)q+1-\frac{c}{\rho p}=0. \tag{12}$$

This equation can be solved either analytically by employing Cardano's formulas or numerically through standard root-searching methods (e.g., Newton-Raphson method).

Uniform demand is often used as a benchmark assumption (Ding et al. (2007)). Accordingly, we solve equation (12) in Appendix EC.1.1 and develop a numerical example in Subsection 3.2.

We conclude this section with an in-depth examination of how the optimal order quantity depends on the supplier's reliability, the firm's risk aversion (or propensity), and the product's onerousness (or profitability). Intuitively, any parametric change that expands the firm's action range should lead to a higher operational level. Thus, we anticipate that increases in supply reliability, risk propensity, and/or product profitability will correspond to a larger order quantity. In a standard NV model, $\mathcal{M}(1,0)$, the critical fractile equation (8) indicates that the optimal quantity increases with product profitability $1-c/p$, or, equivalently, decreases with product onerousness c/p. In a UNV model, $\mathcal{M}(\rho,a)$, the endogenous (*i.e.*, quantity-dependent) bias Ψ in the generalized critical fractile equation (9) influences the impact of onerousness on the optimal order quantity. This effect further depends on the firm's risk aversion a and supply reliability ρ. The intricate relationship among these quantities is unraveled in the following:

Proposition 2 (Properties of the Optimal Order Quantity in a UNV Model)**.** *In a UNV model* $\mathcal{M}(\rho,a)$*, the optimal capacity* q_0^* *increases with the supplier's reliability* ρ*, the firm's risk propensity* a^{-1}*, and the product profitability* $1-c/p$*.*

These properties reflect well-established managerial behavior: a reliable production process facilitates business operations, thereby incentivizing increased activity; a risk-averse firm, acting cautiously, tends to reduce its operations, while a risk-seeking firm behaves in the opposite manner, expanding operations; finally, a company dealing with a highly profitable product is more inclined to order greater quantity, feeling confident in its investment. This proposition also asserts that, for a given order quantity, the three factors—supply reliability, the firm's risk propensity, and product profitability—trade off against one another. Interestingly, the property whereby capacity is increasing in risk propensity may read as decreasing in risk aversion.

2.4. Integrated Risk Management

The problem of IRM in a UNV model $\mathcal{M}(\rho, a)$ amounts to solving an optimization (3) for a selected class $\mathcal{H}$ of financial hedges H that are priced by some valuation method $H \to V^H$. We take up the perspective of a firm having access to an arbitrage-free and complete financial market. For simplicity, we assume a zero risk premium so that the pricing and the physical measures, $\mathbb{Q}$ and $\mathbb{P}$, match. Consequently, any security price is the conditional $\mathbb{P}$-expectation of its (discounted) cash flows H, $V^H(t) = \mathbb{E}^{\mathbb{P}}[H]$. A *feasible hedge* H in a class $\mathcal{H}$ is one fulfilling the firm's budget condition $V^H(t) \leqslant w$. The adoption of a MV target entails a binding budget constraint at the optimal hedge ($V^{H^*}(t) = w$) and we may assume a zero budget ($w = 0$) with no loss of generality.

We consider the cases of no hedging, demand hedging, supply hedging, and combined demand-yield hedging using forward contracts. Appendix EC.2.2 gives a precise description of the related hedging classes $\mathcal{H}_0$, $\mathcal{H}_D$, $\mathcal{H}_Y$, and $\mathcal{H}_{DY}$, and shows that all claims share a common functional form $H(\delta, \upsilon) = \delta D + \upsilon Y + \kappa$. Here, constants δ and υ denote forward holdings and $\kappa = -\delta\mu - \upsilon\rho$ is a cash amount ensuring a zero budget constraint. We identify each hedge H with a forward holding pair according to: $\mathcal{H}_0 \ni H \leftrightarrow (0,0)$, $\mathcal{H}_D \ni H \leftrightarrow (\delta, 0)$, $\mathcal{H}_Y \ni H \leftrightarrow (0, \upsilon)$, and $\mathcal{H}_{DY} \ni H \leftrightarrow (\delta, \upsilon)$.

An IRM policy (q, H) is defined by a control triplet (q, δ, υ) leading to hedged revenues:

$$\Pi_\rho(q, \delta, \upsilon) := \Pi_\rho(q, H) = \pi_\rho(q) + \delta[D - \mu] + \upsilon[Y - \rho], \tag{13}$$

with a slight abuse of notation. The IRM problem (3) featuring a combined forward hedge on demand D and supply yield Y boils down to the nested two-program optimization:

$$\mathscr{U}^*_{DY} := \max_{q \geqslant 0} \left(\max_{(\delta, \upsilon) \in \mathbb{R}^2} \mathbb{MV} \left[\Pi_\rho(q, \delta, \upsilon) \right] \right). \tag{14}$$

By adding a constraint $\upsilon = 0$ or $\delta = 0$, we get to IRM under either demand or supply hedging only, and the corresponding optimal MV targets are denoted by $\mathscr{U}^*_D$ and $\mathscr{U}^*_Y$, respectively. Clearly, a zero budged constraint is implicitly accounted for by the adoption of forward hedges. The inner optimization is a financial hedging problem *conditional* to a value taken by the operational variable q. It leads to an optimal conditional forward hedge. The outer optimization is an operational handling problem corresponding to the optimal conditional forward hedge obtained in the inner problem. More precisely, we have a (1+2)-step algorithm:

Step 1. The *optimal conditional financial hedges* over classes $\mathcal{H}_D$, $\mathcal{H}_Y$, and $\mathcal{H}_{DY}$ are given by:

$$\mathcal{U}_D(q) := \max_{(\delta,\upsilon)\in\mathbb{R}^2:\upsilon=0} \mathbb{MV}[\Pi_\rho(q,\delta,0)] \to \arg\max =: \left(\delta^*_D(q), \upsilon^*_D(q)\equiv 0\right), \tag{15}$$

$$\mathcal{U}_Y(q) := \max_{(\delta,\upsilon)\in\mathbb{R}^2:\delta=0} \mathbb{MV}[\Pi_\rho(q,0,\upsilon)] \to \arg\max =: \left(\delta^*_Y(q)\equiv 0, \upsilon^*_Y(q)\right), \tag{16}$$

$$\mathcal{U}_{DY}(q) := \max_{(\delta,\upsilon)\in\mathbb{R}^2} \mathbb{MV}[\Pi_\rho(q,\delta,\upsilon)] \to \arg\max =: \left(\delta^*_{DY}(q), \upsilon^*_{DY}(q)\right). \tag{17}$$

where $\mathcal{U}_\#(q)$ is the *financially optimal conditional MV target* when hedging in $\mathcal{H}_\#$ ($\# = D, Y, DY$).

Step 2(a). The *order quantity in the optimal IRM* over a class $\mathcal{H}_\#$ ($\# = D, Y, DY$) is given by:

$$q^*_\# := \arg\max_{q\geqslant 0} \mathbb{MV}[\Pi_\rho(q, \delta^*_\#(q), \upsilon^*_\#(q))]. \tag{18}$$

Step 2(b). The *financial hedge in the optimal IRM* over a class $\mathcal{H}_\#$ ($\# = D, Y, DY$) is the optimal conditional financial hedge over $\mathcal{H}_\#$ evaluated at that optimal order quantity over $\mathcal{H}_\#$:

$$H^*_\# = \left(\delta^*_\#(q^*_\#), \upsilon^*_\#(q^*_\#)\right). \tag{19}$$

In conclusion: for a class of financial hedges $\mathcal{H}_\#$ ($\# = D, Y, DY$), the optimal IRM policy is $\left(q^*_\#, H^*_\#\right)$ and the *optimal IRM MV target* is the optimal MV conditional to the optimal order quantity, *i.e.*,

$$\mathcal{U}^*_\# = \mathcal{U}_\#(q^*_\#). \tag{20}$$

A solution to the optimal conditional hedging problems stated as step 1 is given in the following:

Proposition 3 (Optimal Conditional Financial Hedge in a UNV Model)**.** *Consider the IRM problem in a UNV model with demand distribution F_D and a class $\mathcal{H}_\#$ of financial forward hedges with underlying $\# = D, Y,$ or DY. Then, the optimal conditional hedge is given by:*

$$H^*_\#(q) = \delta^*_\#(q)[D-\mu] + \upsilon^*_\#(q)[Y-\rho], \tag{21}$$

with forward holdings $\delta^*_D(q) = \delta^*_{DY}(q) = -\rho p A(q)$ and $\upsilon^*_Y(q) = \upsilon^*_{\rho,DY}(q) = -pB(q)$, and side terms

$$A(q) := \frac{1}{\sigma}\left((q+\mu)\int_0^q F_D(x)\ dx - 2\int_0^q xF_D(x)\ dx\right), \tag{22}$$

$$B(q) = q - \int_0^q F_D(x)\ d. \tag{23}$$

The corresponding optimal conditional MV target is given by:

$$\mathcal{U}_\#(q) = \mathcal{U}_0(q) + \frac{a\rho p^2}{2}\left(\rho A(q)^2 \mathbf{1}_{\{D,DY\}}(\#) + (1-\rho)B(q)^2\mathbf{1}_{\{Y,DY\}}(\#)\right), \tag{24}$$

where $\mathcal{U}_0(q) := \mathbb{MV}[\pi_\rho(q)]$ denotes the MV target of naked revenues conditional to an order quantity q and the indicator function $\mathbf{1}_A(\#)$ equals 1 if $\# \in A$, and 0 otherwise.

The optimal hedges are all short positions because business revenues increase with product demand and supply reliability. Their sizes increase with risk aversion a, with selling price p, and with order quantity q since terms $A(q)$ and $B(q)$ are always positive and increasing ($A(0) = B(0) = 0$ and $\partial_q A(q), \partial_q B(q) \geqslant 0$). Interestingly, if the demand distribution has a density, then any hedging size is convex in order quantity: doubling an order entails more than doubling the notional of any optimal forward hedge. Supply reliability ρ has a positive (resp., negative) effect on demand (resp., supply yield) hedging size. Last, the optimal combined forward holdings match those in the two one-underlying forward hedges since demand and supply yield are independent. In case of mutual dependence, these holding can still be analytically computed by using a general expression derived in Roncoroni and Id Brik (2017).

The order quantity (18) in the optimal IRM solves a further generalized critical fractile equation.

Proposition 4 (Optimal Order Quantity in a Financially Hedged UNV Model)**.** *The optimal order quantity $q^*_\#$ is the unique solution of the IRM generalized critical fractile equation:*

$$F_D(q) = 1 - \frac{1}{\rho(1 - ap\Psi_\rho(q))} \times \left[\frac{c}{p} - h_{a,\rho,\#}(q)\right], \tag{25}$$

where $\Psi_\rho(q)$ is defined in formula (10) and:

$$h_{a,\rho,\#}(q) := \frac{\rho a p}{2}\left(\rho \partial_q A(q)^2 \mathbf{1}_{\{D,DY\}}(\#) + (1-\rho)\partial_q B(q)^2 \mathbf{1}_{\{Y,DY\}}(\#)\right), \tag{26}$$

with $A(q)$ and $B(q)$ given in formulae (22) and (23), respectively.

We conclude by demonstrating that financial hedging does not alter the monotonic properties of optimal ordering with respect to key model parameters.

Proposition 5 (Properties of Order Quantity in the Optimal IRM of a UNV Model))**.** *For any hedging class $\#$ ($\# = D, Y, DY$), the order quantity $q^*_\#$ in the corresponding optimal IRM (expression (18)) increases with supply reliability ρ, the firm's risk propensity a^{-1}, and product profitability $1 - c/p$. Additionally, when a supply yield hedge is used, the order quantity in the optimal IRM vanishes if supply reliability falls below the cost-to-price ratio, i.e., $q^*_Y(\rho) = q^*_0(\rho) = 0$ for all $\rho \leqslant c/p$.*

This result is subtler than it initially appears: while asserting that financial hedging does not change the direction of the effects of key parameters related to production characteristics and firm preferences, it implicitly raises the question of the degree to which these effects are influenced. This intriguing issue lies at the heart of our research on the impact of financial hedging on operational resilience. To the best of our knowledge, it also represents one of the few analytical quantifications of the effect of financial flexibility on operations (*e.g.*, Wang et al. (2024a)).

3. Operational Resilience to Capacity Downsizing

The decision of whether to adopt an IRM approach largely hinges on the influence of financial hedging on optimal physical operations, in particular on operational effectiveness and on operational resilience enhancement .

Operational effectiveness can be measured by the change in the optimal order quantity that results from transitioning between two alternative hedging classes (Guiotto and Roncoroni (2022)). We identify cases in which this variation is nonnegative and instances where it remains unchanged.

Proposition 6 (Operational Effectiveness of IRM in a UNV Model))**.** *Consider the optimal IRM policy in a UNV model $\mathcal{M}(\rho, a)$ over the alternative financial hedging spaces $\mathcal{H}_0, \mathcal{H}_D, \mathcal{H}_Y$, and $\mathcal{H}_{DY}$. Then, for any supply regime $\rho \in [0,1]$, the optimal operational quantity $q^*_\# = q^*_\#(\rho)$ increases with hedge complexity:*

$$q^*_0 \leqslant q^*_D, q^*_Y \leqslant q^*_{DY}. \tag{27}$$

In addition, no financial hedging is relevant for increasing the order quantity above the no-hedging case when the supplier is fully unreliable ($\rho = 0$):

$$q^*_{DY}(0) = q^*_D(0) = q^*_Y(0) = q^*_0(0), \tag{28}$$

and hedging reliability makes no additional contribution when the supplier is fully reliable ($\rho = 1$), irrespective of whether a demand hedge is in place or not:

$$q^*_{DY}(1) = q^*_D(1) \text{ and } \quad q^*_Y(1) = q^*_0(1). \tag{29}$$

This result indicates that no hedge has any impact when the SC is fully unreliable. However, when the SC is partially unreliable, hedging demand and/or supply risk may exert an expansionary effect on physical operations and never lead to a contractionary outcome. This effect may address the issue of underinvestment by upstream firms, identified as the main factor contributing to the insufficient resilience of supply systems, as recently highlighted by Capponi et al. (2024).

Operational resilience enhancement represents a further and particularly striking effect of financial hedging on physical operations. Consider a firm adopting an IRM approach utilizing one of the aforementioned hedging classes. This enhancement occurs when the operational adjustments needed to restore optimality after a disruption are mitigated. Specifically, we aim to show that the optimal IRM featuring a financial hedge against the yield factor Y results in a weaker reaction of the optimal order quantity to any decrease in reliability odds ρ compared to the case of no hedging. Let us formalize this property.

As long as we are concerned with model changes that reflect an SC disruption, regardless of the event causing the shock, the relevant parameter is the supply reliability ρ. We adopt a model risk approach based on sensitivity analysis, where ρ is treated as a deterministic yet unknown parameter (Borgonovo and Plischke (2016)), and we examine changes in model output, here the optimal order quantity, that follow a hypothetical variation in the value of ρ. (This approach contrasts with a Bayesian approach, where model parameters are considered random variables with distributions that can be updated as observations are made.) Any event that harms an SC results in a sudden decrease in the supply reliability parameter, say from ρ_1 to $\rho_2(<\rho_1)$. This change correspondingly modifies all model outputs: the optimal operational quantity declines from $q_0^*(\rho_1)$ to $q_0^*(\rho_2)$ in the case of no hedging (Proposition 2), and from $q_\#^*(\rho_1)$ to $q_\#^*(\rho_2)$ when operating revenues are hedged using a class of claims $\mathcal{H}_\#$ (Proposition 5). Each operational reduction,

$$C_\#(\rho_1,\rho_2) := q_\#^*(\rho_1) - q_\#^*(\rho_2), \tag{30}$$

is referred to as an *operational curtailment* and quantifies the operational effort required to maintain optimality following a disruptive event. Consider two IRM policies featuring financial hedges in classes $\mathcal{H}_1$ and $\mathcal{H}_2$, respectively. We say that $\mathcal{H}_2$-IRM entails a *financially-driven operational resilience enhancement* over $\mathcal{H}_1$-IRM if:

$$C_{\mathcal{H}_2}(\rho_1,\rho_2) < C_{\mathcal{H}_1}(\rho_1,\rho_2). \tag{31}$$

In other words, an SC disruption results in a lower operational effort when revenues are managed using policy $\mathcal{H}_2$ compared to when they are managed using policy $\mathcal{H}_1$.

A benchmark case involves an SC transitioning from full to partial reliability, *i.e.*, from $\rho_1 = 1$ to $\rho_2 < 1$. According to Proposition 6, we have the following insights: (i) Introducing supply yield hedging entails an increase in the optimal order quantity, *i.e.*, $q_Y^*(\rho) \geqslant q_0^*(\rho)$ for all $\rho \in [0,1]$, unless supply is fully reliable, in which case $q_Y^*(1) = q_0^*(1)$; (ii) Any drop in reliability results in a decrease in the optimal order quantity. Thus, the operational curtailments under supply hedging and no hedging are related to one another as follows:

$$C_Y(1,\rho_2) := q_Y^*(1) - q_Y^*(\rho_2) = q_0^*(1) - q_Y^*(\rho_2) \leqslant q_0^*(1) - q_0^*(\rho_2) := C_0(1,\rho_2).$$

This inequality is strict in the viable operational region $[c/p, 1)$. It indicates that hedging against supply yield results in a smaller decrease in the optimal order quantity compared to not hedging, thus demonstrating an enhanced operational resilience driven by suitable financial hedging.

Two natural questions arise: Does this result hold true if the supply was initially unreliable, yet viable, *i.e.*, $c/p < \rho_1 < 1$, and then it worsens as a consequence of an SC disruption, *i.e.*, $\rho_1 \downarrow \rho_2$? What happens in the case where hedging against risk sources other than supply yield, such as demand, is simultaneously in place? We can offer an answer to both questions in the following:

Proposition 7. *Consider a viable business. Then, there exists a threshold $\rho_0 \in (c/p, 1)$ such that for any supply regime drop from ρ_1 to ρ_2 with $\rho_0 \leqslant \rho_2 < \rho_1 \leqslant 1$, an IRM featuring supply hedging ($\mathcal{H} = \mathcal{H}_Y$) enhances operational resilience compared to pure operational handling ($\mathcal{H} = \mathcal{H}_0$):*

$$C_Y(\rho_1, \rho_2) < C_0(\rho_1, \rho_2). \tag{32}$$

Additionally, an IRM featuring a combined demand-supply hedging ($\mathcal{H} = \mathcal{H}_{DY}$) enhances operational resilience compared to an IRM featuring demand hedging alone ($\mathcal{H} = \mathcal{H}_D$).

$$C_{DY}(\rho_1, \rho_2) < C_D(\rho_1, \rho_2). \tag{33}$$

This result demonstrates that operational resilience improves as long as post-disruption supply reliability remains above a certain threshold, which depends on the specific case. An example presented in Subsection 3.2 illustrates the extent to which IRMs with appropriate financial hedges enhance the firm's resilience by mitigating disruption-driven reductions in optimal ordering.

3.1. Efficiency Analysis

The relevance of alternative IRMs can be further appreciated by analyzing their efficiency. This characteristic can be evaluated using efficient frontiers and efficiency profiles. We now describe both metrics, derive an analytical result, and defer a numerical assessment to the next Subsection.

The notion of *efficient frontier* is standard in financial portfolio management. There, the operational variable is represented by a vector of portfolio allocations. In the context of OM, it has been introduced by Wang and Yao (2017) as a way to qualitatively rank alternative classes of IRM policies in terms of the reward-risk trade-off they entail on hedges revenues. Specifically, an efficient frontier is a locus of mean (or, absolute return) and standard deviation (or, risk) pairs

$(m_{\mathcal{H}}(q), \sigma_{\mathcal{H}}(q))$ of financially optimal hedged revenues $\Pi_\rho(q, H^*)$ over a range of operational levels q. In the UNV model, $\sigma_{\mathcal{H}}(q)$ consistently increases with q, while $m_{\mathcal{H}}(q)$ increases until reaching a threshold $\bar{q}_{\mathcal{H}}$, after which it decreases. Return-risk configurations for order quantities exceeding this threshold are inefficient, as they involve both an increase in risk and a reduction in return. Therefore, IRM ranking is grounded on curves obtained by letting order quantity q range between 0 and the smallest order quantity $\bar{q}$ for which at least one of the efficient frontiers reverts to inefficient return-risk configurations, that is $\bar{q} := \min_{\{\mathcal{H}\}} \bar{q}_{\mathcal{H}}$, where $\{\mathcal{H}\}$ denotes an array of hedging classes under exam.

The notion of an *efficiency profile* aims to quantitatively rank alternative classes of IRM policies. In the context of IRM for a standard NV model, this notion has been introduced in Guiotto and Roncoroni (2022) as an adaptation of the Brown and Toft (2002) efficiency index to MV preferences. More precisely, the efficiency profile of a hedging class $\mathcal{H}$ maps an order quantity q to the MV gain of $\mathcal{H}$ relative to the MV gain of combined hedging. In the context of IRM for a UNV model, we modify this notion by defining the efficiency profile as a map of reliability odds ρ to the MV gain of forward hedging (*i.e.*, using either $\mathcal{H}_D$ or $\mathcal{H}_Y$) over the MV gain of combined hedging, *i.e.*,

$$\mathcal{E}_{\#}(\rho) := \frac{\mathcal{U}^*_{\#}(\rho) - \mathcal{U}^*_0(\rho)}{\mathcal{U}^*_{DY}(\rho) - \mathcal{U}^*_0(\rho)}, \qquad \# = D, Y, \tag{34}$$

where the optimal MV targets with hedging $\mathcal{U}^*_{\cdot}$ $(\cdot = D, Y, DY)$ and without hedging $\mathcal{U}^*_0$ are given by (20) and (2), respectively. Here, an explicit dependence of all terms on the reliability ρ has been introduced. The relative efficiency profile $\rho \mapsto \mathcal{E}_{\#}(\rho)$ is well-defined and positive as long as combined hedging provides an upper bound to the MV targets achieved by using either of the two one-underlying hedges, *i.e.*, $\mathcal{U}^*_{DY}(\rho) \geqslant \mathcal{U}^*_D(\rho), \mathcal{U}^*_Y(\rho)$. The resulting ranking enables a firm to evaluate the relative merits of product demand versus supply yield forward hedging.

The appropriateness of transitioning from an IRM with a one-underlying hedge to an IRM with a combined custom hedge should depend on the relative proximity between competing hedges in terms of target performance (Brown and Toft (2002)). Therefore, we can use the relative efficiency of an IRM to determine which is more appropriate—hedging product demand risk or hedging supply yield risk—in an SC context defined by a given reliability ρ. We begin with a definition: an IRM policy is considered *fully efficient* or *inefficient* for a reliability ρ if its relative efficiency is approximately one or zero, respectively.

Proposition 8 (Mean-Variance Efficiency of IRM in a UNV Model)**.** *The optimal IRM with forwards on product demand D is inefficient when production is fully unreliable ($\rho \approx 0$) and becomes fully efficient when production is fully reliable ($\rho \approx 1$). Symmetrically, the optimal IRM with forwards on supply yield Y is inefficient when production is fully reliable and becomes fully efficient when production is fully unreliable.*

This result highlights a significant trade-off between product demand hedging and supply yield hedging. It also indicates that in the extreme cases of full reliability ($\rho = 1$), which encompasses the majority of NV model instances discussed in the OM literature, and supply default ($\rho = 0$), one of the two hedges becomes immaterial. A continuity argument proves the existence of a unique reliability threshold, above which the firm should prefer hedging against demand risk rather than supply risk, and below which it should reverse this preference. We elaborate on the use of these notions in a numerical example.

3.2. A Numerical Experiment

In the setup of Example 2, we consider a firm with risk-aversion coefficient $a = 2 \times 10^{-5}$, facing a demand uniformly distributed as $\mathcal{U}[0, 1000]$ for a product sold at a unit price $p = \$100$ and procured at unit cost $c = \$20$. Here, expected sales amount to 500 product units. The optimal order quantity for naked revenues is derived in Appendix EC.1.1 (formula (EC.3)). When adopting an IRM approach, the optimal order quantity stems from numerically solving the IRM generalized critical fractile equation (25).

Figure 2 presents graphs of optimal order quantities and their curtailment against decreasing supply reliability. These curves represent optimal naked revenues (dotted line) and optimal IRM revenues hedged using forwards on demand (dot-dashed line), on supply yield (dashed line), and combined forwards on demand-supply (solid line). The left panel reveals that: (i) all order quantities decrease as reliability decreases; (ii) they vanish below a critical reliability point, $\rho^c = 20\%$; (iii) above that threshold, all financial hedging strategies lead to an ordering excess over the no-hedge case, regardless of reliability (except for fully reliable supply, where yield hedging becomes inconsequential); (iv) as reliability decreases, this ordering excess consistently deteriorates when hedging demand, while it improves up to a peak at $\rho \approx 42.3\%$ when hedging supply yield, before deteriorating again; (v) at a break-even point, $\rho \approx 69.4\%$, the ordering expansiveness hierarchy

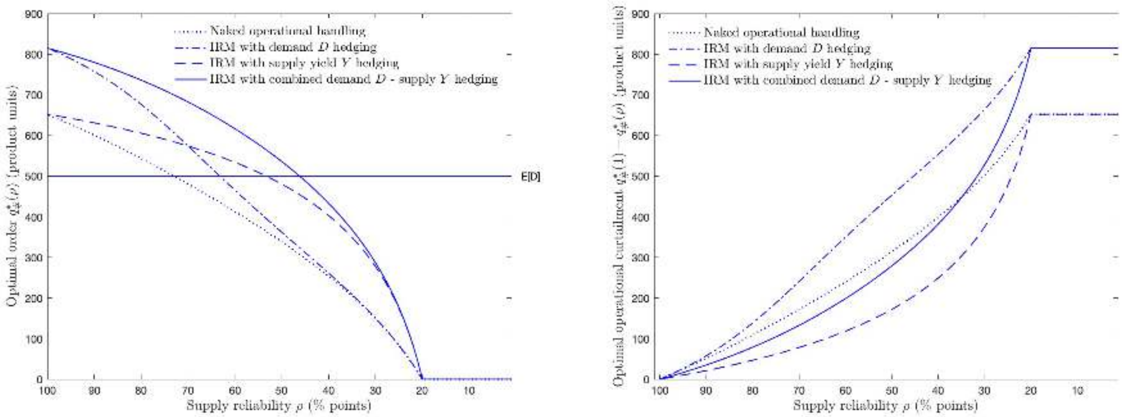


Figure 2 Optimal order quantity profiles $\rho \mapsto q^*_{\#}(\rho)$ (left panel) and operational curtailment profiles $\rho \mapsto q^*_{\#}(1) - q^*_{\#}(\rho)$ (right panel) for optimal naked operational handling ($\# = 0$) and IRM policies ($\# = D, Y, DY$).

of these hedges swaps. This uneven performance of one-underlying hedges presents a dilemma regarding which strategy to adopt. Combining claims resolves this issue, providing consistent performance across the entire reliability range. The right panel shows that all curtailment curves are nonnegative and increase as reliability deteriorates, until they reach the critical reliability point, where orders vanish and curtailments stabilize. The impact of hedging depends on whether supply yield Y is included in the hedging instrument. Although demand hedging is effective in expanding orders, it exacerbates order curtailment compared to the no-hedge scenario, indicating a reduction in operational resilience. This is a significant drawback of demand hedging, which has been overlooked in existing studies. In contrast, supply yield hedging results in the lowest curtailment curve, demonstrating the greatest operational resilience. Notably, this curve is even lower than that of the combined hedge, which is affected by the downside of demand hedging. Yield hedging clearly dominates all other alternatives.

Figure 3 presents graphs that highlight IRM performance in terms of efficiency-related metrics. The left panel shows efficiency profiles $\mathscr{E}_D(\rho)$ and $\mathscr{E}_Y(\rho)$ for optimal IRM policies featuring demand and supply hedges. The profiles clearly reflect the alternative outlined in Proposition 8 and suggest switching from demand to supply hedging when supply reliability is doomed to fall below a break-even point, $\rho \simeq 80\%$. This threshold represents a slight forward shift from the break-even reliability $\rho \approx 69.4\%$ identified in terms of order quantity expansion. As a result, a dilemma arises between whether to ground hedge switching on efficiency or on quantity expansion. This issue can be resolved by turning to operational resilience, which clearly indicates the superiority of yield hedging over

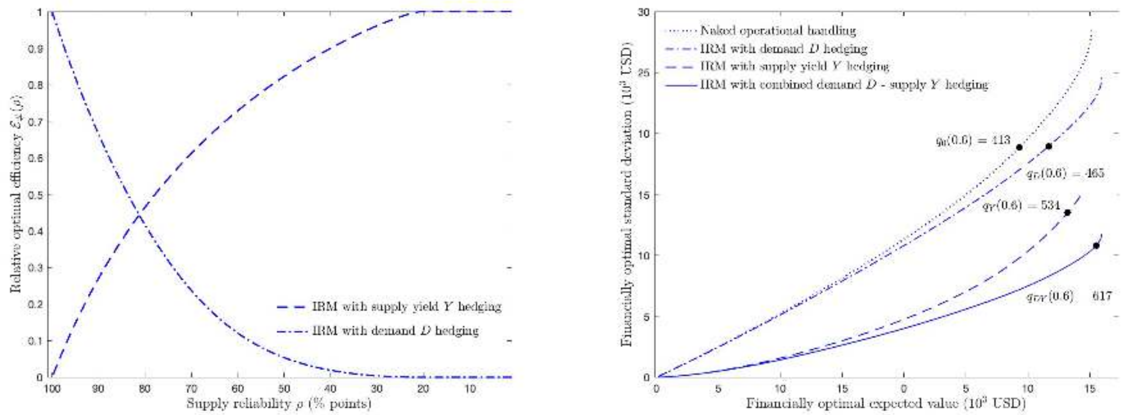


Figure 3 Left panel: Efficiency profiles $\rho \mapsto \mathscr{E}_{\#}(\rho)$ for optimal IRM revenues hedged on demand ($\# = D$) and on supply ($\# = Y$). Right panel: Efficient frontiers $\{(m_{\#}(q), \sigma_{\#}(q)), q \in [0, \bar{q}]\}$ for optimal naked ($\# = 0$) and IRM ($\# = D, Y, DY$) revenues under fair reliability odds $\rho = 0.6$.

demand hedging (Figure 2, right panel). The right panel shows the efficient frontiers for naked and IRM revenues hedged with alternative classes of claims when supply is fairly reliable ($\rho = 0.60$). A bold dot indicates the return-risk point corresponding to the optimal order quantity for the hedging class represented by the curve on which it lies. These graphs show that demand hedging enhances returns without affecting risk (horizontal shift of the bold dot), resulting in a modest increase in optimal capacity by 12.6%, from 413 to 465 units. Supply yield hedging, on the other hand, brings with a sharper increase in returns and a significant decrease in risk, with order size rising by up to 29.2%, from 413 to 534 units. Combined demand-supply hedging leverages the advantages of both one-underlying hedges to varying extents, offering the best return-risk trade-off and an order size increase of 49%, from 413 to 617 product units. Interestingly, demand hedging in this context demonstrates a contribution to risk reduction, despite being immaterial when considered in isolation.

Two key insights emerge from this analysis: (i) An optimal IRM featuring supply yield hedging consistently outperforms any alternative IRM strategy, including combined hedging, across all reliability odds in terms of resilience enhancement. It also surpasses both naked positioning and demand hedging in terms of the return-risk trade-off; (ii) An optimal IRM featuring combined demand-supply hedging outperforms any alternative hedging strategy in terms of order sizing and the return-risk trade-off.

4. An Extension to Capacity Relocation

In a multi-sourcing context, an SC disruption may necessitate operational relocation (Kouvelis et al. (2024)). Resilience can be enhanced by mitigating the need for such relocation. We develop this concept through a novel capacity reshoring model, which we empirically test on the case of gas capacity reshoring from Russia to the U.S. following the 2022 SC disruption.

4.1. A Capacity Reshoring Model

Let a firm commit to selling a product in the domestic market at a future time. Both product demand D and selling price P are random. They allocate production capacity between two facilities, each operating at full capacity. Facility A is fully reliable, supplying a quantity equal to the allocated capacity. Facility B, however, is unreliable: its actual supply may fall short of the installed capacity.

Let the index $i = A, B$ represent either facilities, and q^i denote the production capacity allocated to facility i at the outset (time 0). By assumption, capacity q^A translates into an equal actual delivery, while capacity q^B is subject to a random yield factor Y equal to either 1 (full delivery) or $y \in [0,1)$ (default), resulting in an actual delivery of $q^B Y$ product units. Here, scalar $y \in [0,1)$ identifies a *recovery yield* in case of supply default. We define facility B supply reliability as $\rho := \mathbb{P}(Y = 1)$. Operational costs consist of a constant unit allocation and production term c_i^{cap} $(i = A, B)$, and a variable unit localization cost associated with adapting and transporting products from the production facility to the end market (Ding et al. (2007)). While the localization cost for the unreliable facility is a constant c_B^{loc}, the cost for the reliable facility additively combines a fixed term c_A^{loc} and a market-driven term X, *e.g.*, a commodity price or shipping freight index.

This structure of reliability and costs creates a trade-off in capacity allocation: the firm may choose between a reliable supplier with a fluctuating cost and an unreliable supplier with a predictable cost. Capacity allocation and production costs apply to the entire allocation q^i, while localization costs are incurred only for the actual delivery. The firm prioritizes facility A if $c_R(X) := c_A^{cap} + c_A^{loc} + X < c_B^{cap} + c_B^{loc} := c_B$, and prioritizes facility B otherwise. Operating profits read as:

$$\begin{aligned}\Pi(q^A, q^B; P, D, Y, X) = &\left[(P - c_A^{loc} - X)^+ \min(q^A, D) + (P - c_B^{loc}) \min(q^B Y, (D - q^A)^+)\right] \mathbf{1}_{\{c_A(X) < c_B\}} \\ &+ \left[(P - c_B^{loc})^+ \min(q^B Y, D) + (P - c_A^{loc} - X)^+ \min(q^A, (D - q^B Y)^+)\right] \mathbf{1}_{\{c_A(X) \geqslant c_B\}} \\ &- (c_A^{cap} q^A + c_B^{cap} q^B), \quad (35)\end{aligned}$$

where q^A and q^B are operational control variables, P, D, Y, and X are state variables, and $c_A^{cap}, c_A^{loc}, c_B^{cap}$, and c_B^{loc} are parameters. This model shares the piecewise linear structure of the global allocation model developed in Ding et al. (2007), excluding FX risk (which can be accounted for with minimal additional effort) and including an extension to incorporate supply risk.

The firm optimizes the mean-variance of its revenues over a set of admissible IRM policies, each combining capacity allocations q^A and q^B to facilities A and B, with a financial hedge H to select in a given class $\mathcal{H}$. For a set $Q \times Q \times \mathcal{H}$ of admissible IRM policies, the optimal IRM satisfies:

$$\mathcal{U}_{\mathcal{H}}^* := \max_{(q^A, q^B, H) \in Q \times Q \times \mathcal{H}:\, \mathbb{E}_{\mathbb{Q}}[H]=0} \mathbb{MV}\left(\Pi(q^A, q^B) + H\right) \rightarrow \arg\max =: \left(q_{\mathcal{H}}^{*A}, q_{\mathcal{H}}^{*B}, H_{\mathcal{H}}^*\right). \tag{36}$$

The CRS model IRM optimization (36) decomposes into nested problems:

$$\mathcal{U}_{\mathcal{H}}^*\left(q^A, q^B\right) := \max_{H \in \mathcal{H}:\, \mathbb{E}_{\mathbb{Q}}[H]=0} \mathbb{MV}\left[\Pi(q^A, q^B) + H\right] \rightarrow \quad \arg\max =: H_{\mathcal{H}}^*\left(q^A, q^B\right), \tag{37}$$

$$\max_{(q^A, q^B) \in Q \times Q} \mathbb{MV}\left[\Pi(q^A, q^B) + H_{\mathcal{H}}^*\left(q^A, q^B\right)\right] \rightarrow \quad \arg\max =: \left(q_{\mathcal{H}}^{*A}, q_{\mathcal{H}}^{*B}\right). \tag{38}$$

Problem (37) determines the optimal conditional hedge; problem (38) delivers the operational handling term of the optimal IRM; and the financial hedging term of the optimal IRM stem from inserting operational handling term into the optimal conditional hedge, *i.e.*, $H_{\mathcal{H}}^* = H_{\mathcal{H}}^*\left(q_{\mathcal{H}}^{*A}, q_{\mathcal{H}}^{*B}\right)$.

Suppose that an SC disruption brings about a drop $\rho_1 \downarrow \rho_2$ in the unreliable facility's reliability. This exogenous change typically leads to variations $q_{\mathcal{H}}^{*A}(\rho_2) - q_{\mathcal{H}}^{*A}(\rho_1)$ and $q_{\mathcal{H}}^{*B}(\rho_2) - q_{\mathcal{H}}^{*B}(\rho_1)$ in the optimal operational levels of facilities A and B, respectively. The corresponding operational effort can be measured by the *overall relocation size*, defined as:

$$R_{\mathcal{H}}(\rho_1, \rho_2) := \left|q_{\mathcal{H}}^{*A}(\rho_2) - q_{\mathcal{H}}^{*A}(\rho_1)\right| + \left|q_{\mathcal{H}}^{*B}(\rho_2) - q_{\mathcal{H}}^{*B}(\rho_1)\right|.$$

Consider IRM policies with financial hedging in $\mathcal{H}_1$ and $\mathcal{H}_2$.

We say that optima IRM with hedging in $\mathcal{H}_2$ entails a *financially-driven relocation resilience enhancement* over optimal IRM with hedging in $\mathcal{H}_1$ upon a reliability shock $\rho_1 \downarrow \rho_2$ when:

$$R_{\mathcal{H}_2}(\rho_1, \rho_2) < R_{\mathcal{H}_1}(\rho_1, \rho_2).$$

In summary, an SC disruption leads to a smoother reshoring effort when revenues are managed under an IRM policy with hedging in $\mathcal{H}_2$ compared to an IRM policy with hedging in $\mathcal{H}_1$. In what follows, we focus on situations where a drop in the unreliable facility's reliability leads to a curtailment in its allocated capacity and an expansion in the reliable facility's capacity.

4.2. Operational Resilience to Capacity Reshoring

We empirically test the CRS model and evaluate the ability of IRM to boost relocation resilience upon the European gas SC disruption occurred in 2022. Consider a vertically integrated gas company that previously allocated capacity, operated production, and imported natural gas from the Russian Federation (RF), benefiting from the relatively low costs associated with these operations. Imports were conducted via the two NordStream pipelines crossing the Baltic Sea, with supply risk considered relatively low at the time (German Federal Ministry for Economic Affairs & Energy (2021)). In that context, procuring U.S. Liquid Natural Gas (LNG) was not a viable option due to the high cost of processing, which involves gas liquefaction at −260°F, seaborne shipment under controlled temperature, and subsequent regasification.

The situation changed dramatically with the outbreak of the Russo-Ukrainian war in February 2022, further exacerbated by the sabotage of the NordStream pipelines in September of the same year. These events caused a significant disruption in the gas SC across continental Europe, leading to a sharp rise in gas prices (International Energy Agency (2022)). As a result, U.S. LNG became competitive with inshore gas procurement. The company then faced the decision of whether to allocate gas capacity to the inexpensive but unreliable Russian supply unit, "RF", or to the costly yet reliable U.S.-based supply unit, "US".

We can design a CRS model instance around this trade-off. The selling price of gas is represented as a constant end-consumer tariff p, the market-driven cost term X corresponds to the LNG shipping freight rate for seaborne transportation across the Atlantic Ocean, and the supply costs associated with the reliable U.S. supply are assumed to exceed those of the unreliable Russian supply, *i.e.*, $c_{cap}^{US} + c_{loc}^{US} > c_{cap}^{RF} + c_{loc}^{RF}$. Operating revenues are then expressed as follows:

$$\Pi(q^{US}, q^{RF}) = [(p - c_{loc}^{RF})^{+} \min(q^{RF}Y, D) + (p - c_{loc}^{US} - X)^{+} \min(q^{US}, (D - q^{RF}Y)^{+})] - (c_{cap}^{US} q^{US} + c_{cap}^{RF} q^{RF}). \quad (39)$$

Appendix EC.2.3 reports a comprehensive implementation and calibration of model (39) to historical data. All optimal pure and IRM problems are solved using numerical optimization.

Prior to February 2022, the Russian supply operated in a normal regime ($\rho = 1$). Following the 2022 supply disruption, its reliability decreased to some $\rho < 1$. Consequently, the IRM optimal allocated capacity to Russian supply dropped from $q_{\mathcal{H}}^{*RF}(1)$ to $q_{\mathcal{H}}^{*RF}(\rho)$. The capacity allocated

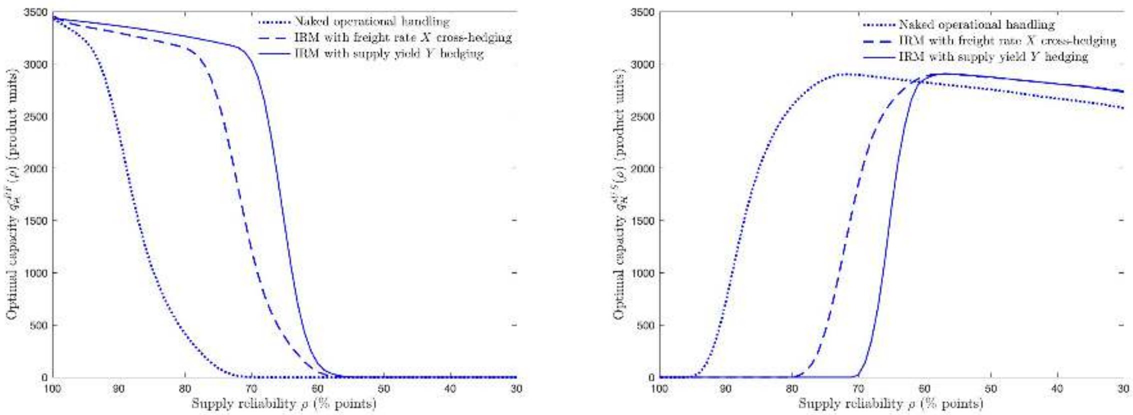
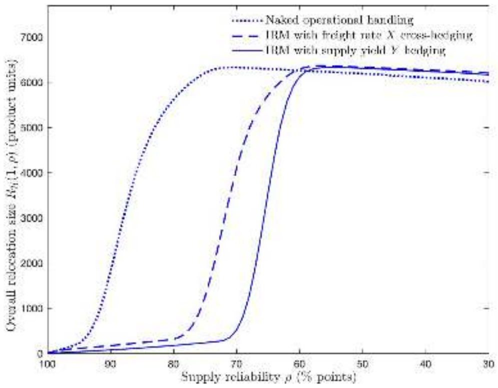


Figure 4 Capacity reshoring. Optimal Russian (left panel) /U.S. (right panel) capacity allocation profiles $\rho \mapsto q^{*RF/US}_{\mathcal{H}}(\rho)$ for optimal naked operational handling and IRM with freight X and supply yield Y forwards.

to U.S. supply experienced both expansion and contraction effects: on one hand, the decreasing reliability of Russian suppliers made U.S. LNG supply relatively more attractive, leading to an increase in U.S. capacity allocation; on the other hand, the negative correlation between Russian supply yield and U.S.-to-Europe LNG shipping freight rates resulted in increased shipping costs for the U.S. supply, exerting a contractionary effect. Overall, the net effect was a capacity expansion of the reliable source, with $q^{*US}_{\mathcal{H}}(\rho) - q^{*US}_{\mathcal{H}}(1) > 0$. This numerical finding aligns with the analytical results of Chopra et al. (2007), which show that a surge in disruption risk is accompanied by increased reliance on the costlier, more reliable supplier at the expense of the cheaper, less reliable one. Figure 4 exhibits the optimal capacity $q^{*RF}_{\mathcal{H}}(\rho)$ allocated to the Russian unreliable supply (left panel) and $q^{*US}_{\mathcal{H}}(\rho)$ allocated to the U.S. reliable supply (right panel) as a function of Russian supply reliability ρ. Allocations refer to naked operational handling ($\mathcal{H} = \mathcal{H}_0$) and to IRM with freight rate X cross-hedging ($\mathcal{H} = \mathcal{H}_X$) and with supply yield hedging ($\mathcal{H} = \mathcal{H}_Y$). These graphs indicate that standalone operational handling requires a sharp reduction in the capacity allocated to the Russian unit once its reliability falls below the relatively high threshold of approximately 95%. In contrast, an ideal forward hedge written on the Russian supply yield Y delays this reduction until the reliability drops to around 65%. A more realistic forward hedge on U.S.-to-Europe LNG shipping freights rate X still enhances operational resilience, though with a higher triggering point of around 75%. In general, financial hedging “postpones” important operational adjustments to regimes with lower reliability odds, thus improving the company’s operational resilience. However, this benefit comes at the cost of a more pronounced capacity curtailment in the Russian facility



	Overall relocation size $R_{\mathcal{H}}(1,\rho)$		
Reliability ρ %	Naked handling	IRM with freight hedging	IRM with supply hedging
100	0	0	0
95	210	109	29
85	4588	239	116
75	6284	1195	239
65	6291	5741	4922
55	6226	6356	6335
45	6139	6299	6270

Figure 5 Operational resilience. Overall relocation size profiles $\rho \mapsto R_{\mathcal{H}}(1,\rho)$ for optimal naked operational handling and IRM with freight X and supply yield Y forwards (left panel) and sample values (right panel).

and a capacity expansion in the U.S. facility at these triggering reliability levels. Interestingly, after U.S. capacity allocation reaches its peak, each capacity allocation curve gradually reverts and declines as Russian supply reliability decreases further. This is due to a net contraction effect driven by the inverse relationship between Russian supply yield and LNG shipping freight rates.

The extent of financially-driven relocation resilience enhancement over the pure operational handling of naked revenues can be assessed by calculating the overall relocation size. In the present CRS model instance, this quantity is defined for each hedging class $\mathcal{H}$ as:

$$R_{\mathcal{H}}(1,\rho) := \left|q_{\mathcal{H}}^{*US}(1) - q_{\mathcal{H}}^{*US}(\rho)\right| + \left|q_{\mathcal{H}}^{*RF}(\rho) - q_{\mathcal{H}}^{*RF}(1)\right|.$$

Resilience is enhanced when $R_{\mathcal{H}_i}(1,\rho) < R_{\mathcal{H}_j}(1,\rho)$ for all $(i,j) = (0,X), (0,Y), (X,Y)$. Figure 5 shows the related size profiles $\rho \mapsto R_{\mathcal{H}}(1,\rho)$, for naked, U.S.-to-Russia freight cross-hedged, and Russian supply hedged revenues (left panel) and sample values in tabular form (right panel). While a drop in Russian supply reliability triggers an almost immediate reshoring effect on a naked business, hedging postpones this impact until the reliability drop exceeds 22 percentage points in the case of cross-hedging using shipping freight forwards and 30 percentage points in the ideal scenario of Russian supply hedging. Beyond these thresholds, the underlying disruption becomes particularly severe, and all relocation efforts tend to converge.

So far, we have examined the effect of financial hedging on capacity reshoring and operational resilience. A firm might wish to couple financial instruments with operational tools to improve these effects. The simplest case involves any action that could increase the recovery yield y in case

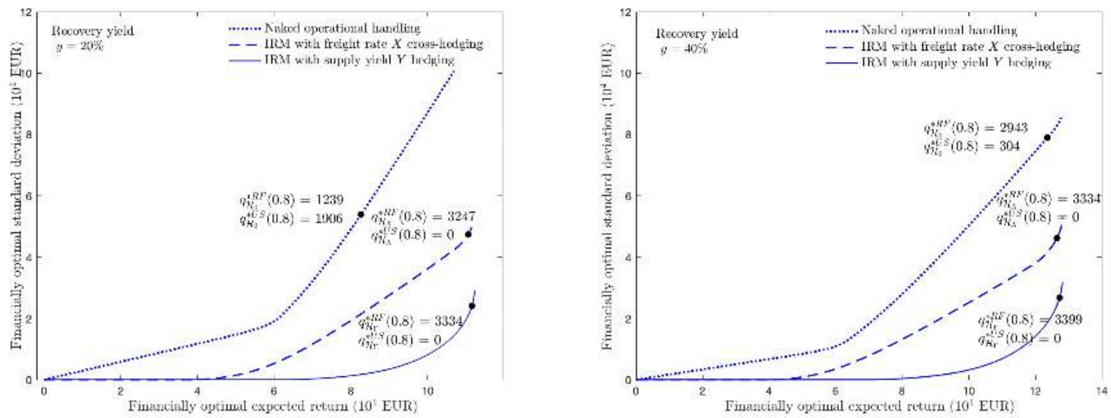


Figure 6 Joint financial hedging and recovery yield handling: Efficient Frontiers for recovery yield $y = 20\%$ (left panel), $y = 40\%$ (right panel), and shared supply reliability ρ=80%.

of supply default. An experiment reported in Appendix EC.1.2 shows that recovery yield handling entails an increase the optimal capacity allocated to the Russian supplying unit for each value of supply reliability ρ. The joint role of financial hedging and recovery yield can be appreciated by analyzing their effect on efficient frontiers. Figure 6 reports frontiers for the cases of naked positioning, cross-hedging, and perfect hedging of supply risk, under a relatively low recovery yield $y = 0.2$ (left panel) and a higher recovery yield $y = 0.4$ (right panel). Here, reliability odds are set to $\rho = 0.80$ in both cases. In both scenarios, hedging consistently offers a leverage to counteract the reshoring effect of the Russian facility supply risk: RF capacity allocation increases at the expense of the U.S.-based production unit. This effect leads to an increase in expected revenues by enabling allocation in the cheaper and more profitable RF unit, despite the associated supply risk. However, the difference between cross-hedging and perfect hedging is primarily confined to the risk reduction side, where the latter definitively outperforms the former. Doubling the recovery yield has an impact on capacity allocation, expected returns, and their standard deviation. However, these effects are significantly stronger in the no-hedging case than in the two hedging cases. Specifically, risk increases more sharply in the naked business relative to the hedged businesses. Symmetrically, this makes hedging increasingly more effective in terms of risk reduction from the no-hedging case. In other words, the operational strategy of increasing recovery yield enhances the risk-reduction power of financial hedging, further strengthening its role in mitigating supply chain risks. A further (and subtler) interaction between the operational handling of recovery yield and financial hedging is discussed in Appendix EC.1.2.

5. Conclusion

5.1. Summary and Managerial Considerations

We conjecture that IRM can enhance operational resilience to supply disruptions. This model risk hypothesis is examined within the context of capacity planning across one or two sourcing entities. Our analysis identifies financial hedges that mitigate operational shifts, such as sourcing contraction (downsizing) or relocation (reshoring), resulting from disruptions that impair supply reliability. We validate our conjecture using an unreliable supply newsvendor model and a capacity reshoring model: with the former, we analytically prove that appropriate hedging (or even cross-hedging) of supply risk (a) counterbalances capacity allocation shrinkage due to supply disruptions and (b) significantly reduces this operational contraction compared to purely operational strategies, thereby enhancing operational resilience; with the latter, we empirically show that a suitable hedge of supply risk can reduce the extent of capacity reshoring required by the European gas supply chain disruptions following the 2022 Russo-Ukrainian war outbreak. Furthermore, we reveal that traditional IRM strategies based on demand hedging may intensify the operational adjustments required by a supply chain disruption, thereby increasing operational fragility. We argue that our IRM approach to operational resilience may provide distinct advantages in flexibility, timing, and cost savings, making it a valuable complement to conventional operational tools.

Three major assumptions in the UNV model may limit the practical application of its prescriptions in real-world scenarios: (1) full knowledge of supply reliability ρ; (2) the ability to trade derivatives written on product demand D and supply yield Y; and (3) the one-period setup. In practice, ρ is often unobservable, D and Y are nonclaimable, *i.e.*, financially uninsurable, and a reliability drop would necessitate hedge updating at an intermediate point in time. The first issue can be addressed either by estimating a proxy for reliability odds, such as the Overall Equipment Effectiveness (OEE) index, or by adopting a conservative approach based on a worst-case scenario. The second issue can be tackled using the cross-hedging approach proposed by Gaur and Seshadri (2005). The third issue may be resolved by either extending the model to a multi-period framework or incorporating into end-of-period business revenues the P&L from financial hedge transitioning from $H^*_{\#}(\rho_1)$ to $H^*_{\#}(\rho_2)$ following a reliability drop $\rho_1 \downarrow \rho_2$. Appendix EC.1.3 provides a detailed elaboration on these solutions, including a few technical specifics.

5.2. Future Developments

Future research could explore theoretical advancements and practical applications.

A first research direction could explore the case of outsourced procurement (Dada et al. (2007)). This scenario involves paying costs only for the actual supply qY. While this may appear to be a minor adjustment, it introduces significant analytical complexity: a drop in supply reliability generates competing effects—reducing the order size, as in our UNV model, and increasing it to compensate for lower yield, with no cost incurred for undelivered items. *A priori*, the net effect is uncertain, as is the impact on the effectiveness of a financial approach to operational resilience.

A second research direction could incorporate statistical dependence between supply yield Y and product demand D, a realistic yet underexplored scenario. Examples include Babich (2010) (joint capacity ordering and financial subsidy policies), Allon and Van Mieghem (2010) (base-surge sourcing in offshore-nearshore sourcing), Sting and Huchzermeier (2012) (dual sourcing analysis), Boyabatli and Feng (2024) (joint capacity investment and hedging decisions), and Wang et al. (2024b) (preference for expensive over cheaper suppliers under demand-supply correlation). We conjecture that demand-supply correlation may mitigate, or even invert, the fragility effect of demand hedging. Additionally, it causes combined hedging to deviate from a simple assemblage of optimal forwards (Guiotto and Roncoroni (2022)), necessitating the evaluation of the effectiveness of genuine combined forwards (Roncoroni and Id Brik (2017)).

A third research direction could extend our results to a dynamic framework, either in discrete time (Kouvelis et al. (2018)) or continuous time (Caldentey and Haugh (2006); Wang and Yao (2017)). Such extensions would allow for differentiating between disruption risk, modeled via regime changes, and normal supply risk, captured through jump terms. Additionally, they could enable distinguishing between permanent and temporary disruptions by incorporating recovery probabilities. Furthermore, these extensions would facilitate an analysis of the trade-off between execution costs and resilience benefits when transitioning from static to dynamic hedging.

Other research directions could focus on relaxing the constraints of our model, such as allowing for market incompleteness (Gaur et al. (2011)) or exploring alternative target objectives, such as expected utility (Chod et al. (2010)) or CVaR (Zhao and Huchzermeier (2017); Wang et al. (2024b)). Finally, our model could be integrated into a general equilibrium production network (Pellet and Tahbaz-Salehi (2023), Como et al. (2024)), to provide insights into the systemic implications of operational and financial resilience strategies.

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