Efficiency or resiliency?
Corporate choice between financial and operational hedging*

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Abstract

We propose and model that firms face two potential defaults: *Financial default* on their debt obligations and *operational default* such as a failure to deliver on obligations to customers. Hence, firms with limitations on outside financing substitute between saving cash for financial hedging to mitigate financial default risk, and spending on operational hedging to mitigate operational default risk. Whereas financial hedging increases in financial leverage, operational hedging declines in leverage. This results in a positive relationship between operational spread (markup) of the firm and its financial leverage or credit risk, which is stronger for firms facing financing constraints. We present empirical evidence supporting the relationship by employing two proxies for operational hedging, viz., inventory and supply chain diversification, exploiting recessions and the global financial crisis as exogenous correlated shocks to operational and credit risks.

KEYWORDS: FINANCIAL DEFAULT, OPERATIONAL DEFAULT, RESILIENCE, LIQUIDITY, RISK MANAGEMENT, INVENOTRY, SUPPLY CHAINS, SUPPLY CHAIN DIVERSIFICATION

JEL: G31, G32, G33

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1. Introduction

The Covid-19 crisis has raised the issue of corporate resilience to shocks following disruptions in supply chains which adversely affect operations. Companies tackle such negative supply-chain shocks by operationally hedging against them. Such hedging includes diversifying the supply chains by allocating resources to increase the pool of suppliers and shifting some of them to nearby, more secure locations; maintaining backup capacity; and, holding excess inventory. In essence, companies endure a higher cost of production — through holding spare capacity and excess inventory, or rearranging their supply chains — in order to mitigate the risk of operational disruption.

A global survey by the Institute for Supply Management finds that by the end of May 2020, 97% of organizations reported that they would be or had already been impacted by coronavirus-induced supply-chain disruptions.[1] Consequently, U.S. manufacturing was operating at 74% of normal capacity, with Europe at 64%. The survey also finds that while firms in North America reported that operations have or are likely to have inventory to support current operations, confidence had declined to 64% in the U.S., 49% in Mexico and 55% in Canada. In Japan and Korea too, many firms were not confident that they will have sufficient inventory for Q4; and, almost one-half of the firms are holding inventory more than usual. In response, 29% of organizations were planning or have begun to re-shore or near-shore some or most operations.[2] However, such operational resiliency is not being favored by all firms as several corporate chief executive officers (CEOs) and investors contend that operational hedging is costly and occurs at the cost of financial efficiency.[3]

Our paper studies one aspect of the tension between operation resiliency and financial efficiency, viz., the tradeoff between the firm's allocation of cash to operational hedging and

[1] `https://www.prnewswire.com/news-releases/covid-19-survey-round-3-supply-chain-disruptions-continue-globally-301096403.html`. See also "Businesses are proving quite resilient to the pandemic", The Economist, May 16th 2020, and "From 'just in time' to 'just in case'", Financial Times, May 4, 2020.

[2] "Reshoring" and "nearshoring" are the processes of bringing the manufacturing of goods to the firm's country or a country nearby, respectively.

[3] "Will coronavirus pandemic finally kill off global supply chains?" Financial Times, May 27, 2020. `https://www.ft.com/content/4ee0817a-809f-11ea-b0fb-13524ae1056b`

to the prevention of financial distress. While operational hedging may be beneficial on its own, it may compete for resources with the firm's demand for financial hedging. The need to optimally balance these two hedging needs — operational hedging and financial hedging — can help explain the lack of operational resilience in some firms.

In our theoretical setting, a competitive (price-taking) levered company faces two important risks. First, it faces a risk of financial default, because cash flows from assets in place are risky. Second, the firm faces the risk of operational default, such as failing on an existing commitment to deliver goods to costumers. The two risks — financial default and operational default — are possibly correlated. For example, an aggregate shock may affect the firm's cash flows, possibly enough to induce financial default, as well as the firm's suppliers, who may be unable to deliver to the firm, in turn causing the firm to default on its contract to deliver goods to its customers. Both financial and operational defaults lead to some loss in the franchise value of the firm.

The firm can use its cash inflow to build up cash buffers and mitigate the risk of financial default. The firm can also use the cash inflow to increase the likelihood that it will deliver on its promise to customers by allocating resources to operational hedging that includes holding excess inventory, maintaining backup capacity, and incurring greater expenses on supply chains. Naturally, such operational hedging raises the firm's cost of production or reduces its *operational spread*, viz., the "markup" or the price-to-cost margin per unit. Even an unlevered firm will in general optimally choose an interior level of operational hedging in order to protect its profitability while recognizing that an operational default leads to a loss of its franchise value.

Interestingly, as operational hedging reduces the risk of delivering to the firm's customers, it can potentially also reduce the risk of financial default by raising the level of its future cash flows. However, this is feasible only if the firm can pledge the benefits of operational hedging to outside investors. If pledgeability is low, financial and operating hedging become substitutes: In other words, a firm that faces difficulty in raising funds must decide between using cash to mitigate the risk of financial default, or maintaining spare capacity, holding excess inventory, or spending cash on contracting with higher-cost suppliers.

Our principal theoretical result is that for a firm with higher default risk and difficulty in raising capital, the optimal amount of operational hedging decreases with the firm's *credit spread* which is increasing in financial default risk. Operational hedging also reduces the operational spread (markup) as it increases firm's cost of production. In other words, the firm optimally sacrifices operational resiliency for financial efficiency. This creates a *negative relation between the credit spread and the operational spread.* More financial hedging that reduces the credit spread also reduces operational hedging and this is reflected in a wider markup. Similarly, our model also predicts that higher existing leverage is associated with a wider markup. This positive relation between leverage and markup is muted, possibly even reversed, for for firms with no perceived financing problem, as they can engage in operational hedging and simultaneously pledge superior operating cash flows to avoid financial default.[4]

We provide empirical tests of our model's predictions on the tradeoff between operational hedging and credit risk, or specifically, between the operational spread (markup) and financial leverage or measures of credit risk, and relate that to firm's financing restrictions or constraints. We do so by employing two measures of operational hedging, viz., inventory and supply chain diversification, and exploiting recessions and the global financial crisis as correlated sources of risk to credit and operational risks.

We start by studying the firm's markup or operational spread, measured as sales minus cost of goods sold (CGS) divided by sales. This is effectively the (negative of) CGS scaled by sales, which by our model increase for firms that are engaged in greater operational hedging. As expected, we find that Markup declines in proxies for the level of operational hedging: higher inventory and greater supply chain diversification, which raise costs, lower Markup. In particular, we employ two measures of supply chain diversification: supply chain diversification index, the first principal component score from a principal component analysis, and supply chain diversification ranking, the negative value of the average ranking, all of which based on three individual measures: number of suppliers, number of supplier

[4]In our model, the effect of leverage on operational hedging is due mostly to lack of funds to invest, and not simply due to debt overhang (lack of incentives to invest due to leverage, as in Myers (1977)).

regions, number of suppliers that are not from the firm's region.[5] This evidence supports the use of markup as a summary measure of the extent of operational hedging that the firm engages in. We then examine whether leverage and credit risk are correlated with the markup in the way predicted by our model.

We find that higher leverage and higher credit risk, measured using Altman's Z-score (Altman, 2013), which necessitate allocation of cash to financial hedging, are positively related to the markup, implying a reduction in operational hedging. To gauge the economic significance of the effect, one standard deviation increase in the firm's negative z-score raises the firm's markup by 13% of the sample median markup. To deal with the endogeneity of financial leverage, we examine the near-term portion of long-term debt, which can be considered to be exogenous to the current state of the firm, having been determined in the past when it was issued. We find that the positive relation between the markup and leverage is stronger for the short-term portion of the long-term debt which matures in the next two years. Higher short-term portion of the long-term debt raises the markup about twice as strongly as does long-term debt. This is consistent with our model by which the near-term need to avert financial default diverts funds from longer-term operational hedging, and this is reflected in a wider operational spread when there is more long-term debt due.

The robustness of this result is examined by controlling for the effect of the firm's market power, which is known to affect the firm's markup because market power enables firms to raise prices. We find that the effect on markup of credit risk or liquidity needs remains positive and significant even after controlling for the effects of market power. We further test another important prediction of our model that the positive markup-credit risk relationship is stronger for firms that are subject to financing frictions and financial constraint which we measure by the need to hoard cash, after controlling for other motives of cash holdings. Our choice of using firms' precautionary cash balances to measure their degrees of financial constraints are motivated by recent research (e.g., Buehlmaier and Whited, 2018), who find

[5] As a validation of our operational hedging measures, Appendix IA.2 has shown that supply chain diversification is indeed a means to mitigate operational risk: Firms with more diversified supply chain networks are less exposed to adverse industry-wide shocks, measured by negative industry returns.

that highly constrained firms, according to their textual measures, hold remarkably higher cash balances. We indeed find that the positive markup-credit risk relationship is significant mainly for firms with higher lagged cash holdings, our proxy for financial constraints.

Moreover, we use two time-series variations in financing conditions to identify situations in which credit risk should have a stronger effect on operational hedging and thus markup. First, we find that the positive correlation between markup and credit risk is more pronounced during the recession periods designated by NBER, and is concomitant with a more pronounced negative correlation between inventory holding and the credit risk. Recessions are also times when shocks to credit and operational risks correlate, as is the starting premise of the model. Second, we consider time-series variation in financial conditions by studying the effect of an exogenous shock to the credit supply of firms. We follow Chodorow-Reich (2014) who studies the negative impact of the subprime mortgage crisis and Lehman Brothers' collapse on lenders' abilities to extend credit to borrowers. A firms's exposure to this shock, in terms of its relationship banks being affected by the shock, reflects an increase in financing frictions. We find that exposed firms that were more highly levered prior to the crisis reduced operational hedging, i.e., increased their markup, by more than less exposed firms. This test also helps address concerns about the endogeneity of financial leverage in that existing literature on the impact of the financial crisis has shown that pre-crisis leverage is an important pre-condition that determined post-crisis real effects through a liquidity demand channel (e.g., Giroud and Mueller, 2016). We also find, to a lesser extent, that firms with more precarious liquidity positions before the crisis cut back inventory holdings and supply chain diversification in post-crisis era, if their lenders are more adversely affected by the crisis.

Broadly speaking, our contribution in this paper is to study both theoretically and empirically the determinants of operational hedging and its tradeoff with financial hedging, especially for firms facing financial constraints. To our best knowledge, the positive relationship between operational spread (markup) and financial leverage or credit risk has not been documented in the prior literature.[6]

Our paper is related to studies of the real effects of financing frictions (see Stein (2003) for a review) which show that financing frictions can affect investment decisions and employment (Lemmon and Roberts, 2010; Duchin et al., 2010; Almeida et al., 2012; Giroud and Mueller, 2016, among others). The literature also studies the effect of financial constraints and financial distress on financial policies such as cash, credit lines, and risk management (e.g., Almeida et al., 2004; Sufi, 2009; Bolton et al., 2011; Acharya et al., 2012). Our paper relates closely to those of Rampini and Viswanathan (2010) and Rampini et al. (2014), who show that more distressed firms may reduce risk management in order to preserve debt capacity for investment and other current expenditures. These studies focus on financial hedging through derivatives while our focus is on operational hedging.

Our paper also relates to Froot et al. (1993), who propose a theory for the rationale for corporate hedging. In Froot et al. (1993), hedging against cash shortfalls helps the firm mitigate the risk of not being able to finance valuable investment opportunities. In a more recent paper, Gamba and Triantis (2014) studies firms' risk management policies through holding liquid assets (cash equivalent), purchasing financial derivatives, and maintaining operational flexibility. They demonstrate that the strongest motivation for hedging is to avoid financial distress. They show in the model that the three risk management tools are more of complements than substitutes, and cash holding is the most effective out of these three risk management mechanisms. We instead propose a parsimonious model of operational hedging. In our model and empirical tests, we highlight that the mismatch between cash inflow and outflow due to financial obligations can make financial hedging and operational hedging substitutes. In our model, operational hedging is not a means to avoid financing shortfall, but it is rather the other way around: Hedging against a shortfall of cash that presents a financial default risk reduces the resources allocated to operational hedging for firms facing financial constraints or having low pledgeability of cash flows.[7]

[6] In a related but different context, Hankins (2011) finds evidence that bank holding companies reduce financial hedging following diversifying acquisitions.

[7] See Bianco and Gamba (2019) for a recent theoretical contribution focusing on the risk management role of inventory. They focus on an all-equity firm so do not analyze the effect of credit risk on operational

Studies of the relationship between a firm's credit risk and its markup (e.g., Gilchrist et al., 2017; Dou and Ji, 2020; Meinen and Soares, 2021) propose that firms that need to increase short-term profits to meet their liquidity needs may raise their product price and thus their markup. Such an ability to extract higher profit by raising prices implicitly assumes market power. Our analysis controls for market power which is known to be positively associated with the firm's markup. We find that the effect of market power on the markup is indeed larger for firms facing higher external financing frictions, and we find that our model's predicted positive association between the markup and leverage or credit risk persists even after controlling for market power.

2. The model

2.1 Model setup

This section develops a model of a competitive (price-taking) levered firm's optimal operational hedging policy in the presence of costly financial default (default on debt service) and operational default (default on the supplier contract). Our main goal is to show that firms can face tensions between operational hedging and financial hedging, where we model financial hedging as saving cash in order to avoid default on its debt maturing before the settlement date of supplier contract.

Our model introduces operational hedging in the setting of Acharya et al. (2012). The model features a single-levered firm with existing debt F in a three-period economy: $t = 0$, 1, 2. The firm has assets in place that generate a cash flow x_t at each period $t = 0$, 1. x_2 represents the franchise value. Additionally, the firm has an outstanding supplier contract that stipulates a delivery of I units of goods at unit price p at $t = 2$.

There is a random shock u that affects both the firm's cash flow at $t = 1$ and its capacity to fulfill the supplier contract. The latter impact can be due to supply chain disruptions. In this sense, u is a systematic shock. The value of u is realized at $t = 1$. Specifically, the firm's

hedging as we do.

cash flow at $t = 1$ is given by $x_1 = \bar{x}_1 + u$, and its production capacity is reduced from I to $(1 - \delta(u))I$, where $\delta(u)$ is decreasing and convex in u with continuous and finite first and second order derivatives. The probability distribution of u is given by the density function $g(u)$ with support $[0, \infty)$, the associated cumulative distribution function being $G(u)$ and the hazard function $h(u)$ being defined as

$$h(u) = \frac{g(u)}{1 - G(u)} \ . \tag{2.1}$$

To derive analytical solutions, we assume that u is exponentially distributed on $[0, \infty)$ with density function $g(u) = \alpha e^{-\alpha u}$. Then the cumulative distribution function $G(u) = 1 - e^{-\alpha u}$. Notably, the hazard function $h(u)$ is a constant α.[8] Figure 1 illustrates the timeline of the model.

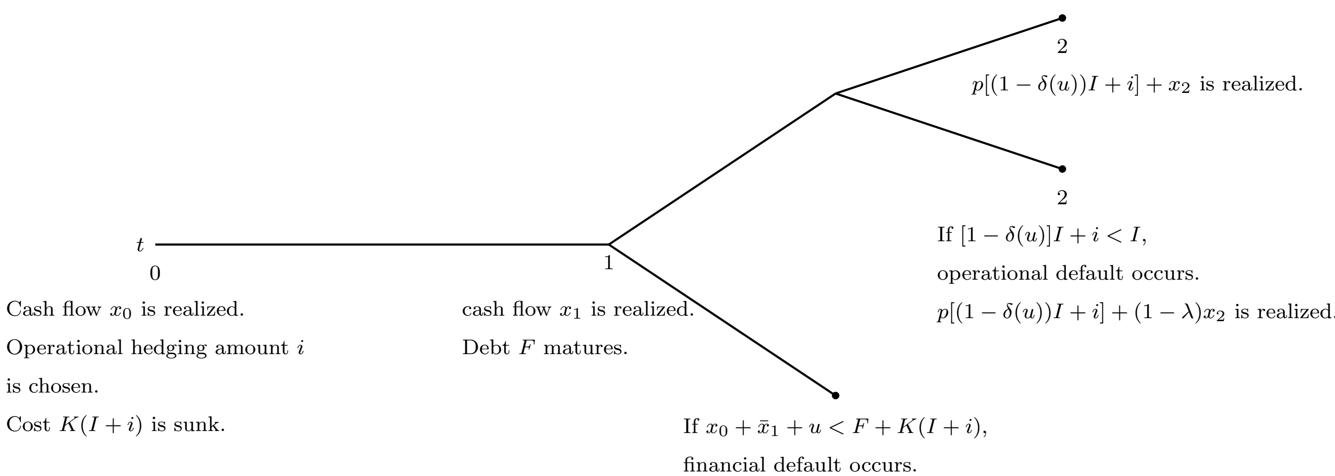

Figure 1: The timeline of the model

At date $t = 0$, the assets in place generate a positive cash flow $x_0 > 0$. In the meantime, the firm starts producing I units of goods scheduled for delivery at $t = 2$. Moreover, the firm can choose to hedge the operational risk by making a marginal investment i, resulting in the total units of delivered goods being $(1 - \delta(u))I + i$. i can also be interpreted as inventory, and/or spare production capacity.[9] The cost of the production and operational hedging is

[8]Exponential distribution is a special case of Gamma distribution, which has been widely used to model the jump size distribution of uncertainty shocks in finance (e.g., Johnson, 2021).

[9]In our model the firm is operationally inflexible in the sense that its production amount is confined by

summarized by an increasing and convex cost function $K(I+i)$ with continuous and finite first and second order derivatives. We assume that the firm is a price-taker in its supplier contracts.

We assume that market frictions preclude the firm from accessing outside financing at $t=0,1$. Thus, the firm's disposable cash at date-0 comes entirely from its internal cash flow. Thus, the cash reserve is $c=x_0-K(I+i)$. At $t=1$, the firm must make a debt payment of F, which is assumed to be predetermined (a legacy of the past). We assume that debt cannot be renegotiated due to high bargaining costs; for example, it might be held by dispersed bondholders prone to coordination problems. Notice that the debt payment must be made out of the firm's internal funds. Failure to repay the debt in full at $t=1$ results in financial default and liquidation, in which case future cash flow from the contractual delivery investment, $p[(1-\delta(u))I+i]$, and the franchise value, x_2, are lost. Since the period-1 cash flow, x_1, is random, there is no assurance that the firm has enough liquidity to repay the debt in full. Moreover, failure to deliver I units of goods results in operational default, leading to a loss of the franchise value, x_2, by a portion $\lambda\in[0,1)$. This can be interpreted as, for example, a reputation loss with its customers who can switch to alternate suppliers.

2.2 Discussion

Before proceeding further, we want to stress that the exact specification of the model can vary widely without affecting the results qualitatively, as long as four assumptions are satisfied. First, default involves deadweight costs to shareholders. Although we assume that all future cash flows are lost in default, an extension to a partial loss is straightforward. Second, the outstanding debt matures before the supplier contract settlement date, giving rise to a maturity mismatch between debt contract and supplier contract. Moreover, external financing cannot be raised against the majority of income from the supplier contract settlement at date-2. If the firm can pledge a large enough fraction of its income from fulfilling the supplier contract as collateral, then current and future cash holdings can be viewed as time

the size of the customer contract. We do so to isolate the firm's operational hedging decisions.

substitutes, and there is no role for precautionary savings of cash. As a result, the tension between financial hedging and operational hedging breaks down. In reality, the condition of partial pledgeability is likely to be universally met. While the base case model assumes that external financing is prohibited, Section 3.1 extends the model by allowing the firm to borrow up to a certain fraction τ of its cash flow from contract settlement at $t = 2$, and shows that our main results hold as long as τ is sufficiently small, i.e., the pledgeability level is sufficiently low. The bankruptcy cost to shareholders, coupled with debt-cash flow maturity mismatch and limited liability, create incentives to hold liquidity resources for the financial hedging purpose. Lastly, the shock at $t = 1$, in additional to make the cash flow at date-1 fall short of the debt contract obligation, can also make the production capacity fall short of the supplier contract obligation, leading to a loss to the franchise value. This creates the incentive for operational hedging. The two hedging activities are subject to the firm's budget constraint. Although we assume a single uncertainty state affects both the cash flows from assets in place and its production capacity, extending our model to different sources of uncertainties is possible.

Finally, shareholders may find it optimal to raise debt maturing at $t = 1$ that is more senior than the existing debt and invest in operational hedging. This occurs when sensitivity of function $\delta(u)$ with respect to u and the cost of operational default (captured by λ) are both sufficiently high.[10] In our base case model, we assume that financing constraints at $t = 0$ preclude the firm from accessing any additional financing. Explicitly modeling debt maturity structure polices at date-0 is an interesting extension of our model.

2.3 Optimal hedging policies

In general, the firm has a positive amount of existing debt ($F > 0$). The firm's optimal hedging policy depends on the relative likelihood of financial default to operational default, which, in turn, depends on the relative magnitudes of shock thresholds that triggers financial

[10]By contrast, as in Acharya et al. (2012), raising debt maturing at $t = 1$ solely to increase the cash reserve is value-neutral in this setting, as the increase in cash is exactly offset by the increase in the required debt repayment (i.e., cash is negative debt in this setting of "short-term" debt).

and operational defaults.

The amount of cash available for debt service at date 1 is $x_0 - K(I+i) + x_1$, where $x_0 - K(I+i)$ is the cash reserve and $x_1 = \bar{x}_1 + u$ is the interim-period cash flow from assets. The "financial default boundary", u_F, is the minimum shock level that allows the firm to repay F in full and avoid default:

$$\begin{aligned} u_F &= F + K(I+i) - x_0 - \bar{x}_1 \\ &= \bar{F} + K(I+i) \ , \end{aligned} \tag{2.2}$$

where $\bar{F} = F - x_0 - \bar{x}_1$ is the net debt, i.e., debt minus date 0 and 1 predictable cash flows. The financial default boundary u_F increases with the level of net debt $(\bar{F})$ and operational hedging amount (i). For all realizations of u between 0 and u_F, the firm defaults on its debt contract and equity holders are left with nothing.

We also allow the firm to default on the supplier contract. The amount of goods that the firm can deliver at date-2 is $(1 - \delta(u))I + i$. If this amount is less than the production commitment I, the firm defaults on the supplier contract. Correspondingly, the "operational default boundary", u_O, is the minimum shock level that allows the firm to deliver its contractual amount of goods in full and avoid operational default:

$$\begin{aligned} (1 - \delta(u_O))I + i = I, \ \text{or} \\ u_O = \delta^{-1}\left(\frac{i}{I}\right) \ . \end{aligned} \tag{2.3}$$

Since the loss function δ is decreasing in u, its inverse function δ^{-1} is decreasing in i. This means that the operational default boundary u_O is decreasing with i, the amount of operational hedging the firm chose at date-0. In this sense, operational hedging reduces the operational default risk. For all realizations of u between 0 and u_O, the firm defaults on its supplier contract and equity holders lose a portion λ of the franchise value x_2.

Define $D(i, \bar{F})$ as the difference between financial and operational default thresholds for given net debt level $\bar{F}$ and operational hedging policy i:

$$D(i,\bar{F}) \equiv u_F - u_O = \bar{F} + K(I+i) - \delta^{-1}\left(\frac{i}{I}\right) \ . \tag{2.4}$$

In the remaining of this subsection, we solve for the firm's optimal operational hedging policy. The detailed proofs are in the Internet Appendix.

2.3.1 Benchmark: Optimal hedging policy when $F = 0$

Consider first a benchmark case when the debt level $F = 0$. In this case, financial default is irrelevant: $u_F = 0$. The firm will choose the hedging policy $\bar{i}$ that maximizes the unlevered date-0 equity value:

$$\bar{E} = \int_0^{\infty} \Big[x_0 - K(I+i) + \bar{x}_1 + u + p\left[(1-\delta(u))I + i\right] + x_2\Big] g(u)du - \int_0^{u_O} \lambda x_2 g(u)du \ . \tag{2.5}$$

The last term of Equation (2.5) reflects the proportional loss of franchise value in case of operational default. The first-order condition is

$$\frac{\partial \bar{E}}{\partial i} = p - K'(I+i) - \lambda x_2 \frac{g(u_O)}{I\delta'(u_O)} = 0 \ , \tag{2.6}$$

where $u_O = \delta^{-1}\left(\frac{i}{I}\right)$. Define $\bar{i}$ being the solution for the first-order condition (2.6). In Appendix IA.3, we show that $\bar{i}$ is also the unique optimal hedging level that maximizes the equity value (2.5), under mild technical conditions.

The following assumption ensures that the firm has enough cash flow at date-0 to choose the highest possible optimal operational hedging, which occurs when the firm is debt-free. It also ensures that u_F is continuous in $\bar{F}$ and $u_F = 0$ for sufficiently small $\bar{F}$:

Assumption 2.1.

$$K(I+\bar{i}) < x_0 + x_1 \ . \tag{2.7}$$

Since $D(i,\bar{F})$ is continuous in $\bar{F}$, u_F is always smaller than u_0 regardless of the value of

i for sufficiently small $\bar{F}$.

As will be clear later, operational default boundary u_O only enters into equity value function if it is larger than the financial default boundary u_F. Thus, the main challenge in solving the model is that both u_F and u_O are endogenously determined by the firm's hedging policy. In what follows, we first solve for the firm's optimal hedging policy that maximizes the equity value; then we characterize the relationship between the hedging policy and the net debt level.[11] We do this in steps by considering the relative position of thresholds for financial and operational defaults, u_F and u_O, respectively, and then addressing its endogeneity to hedging policy and model primitives (such as leverage).

2.4 Optimal hedging policy when $u_F \geq u_O$

If the firm's inherited debt level is so high that the financial default boundary is greater than the operational default boundary, then the firm would have already declared financial default at date-1 for the shock values that would trigger the operational default. Thus, operational default boundary does not enter the equity value function in this case. The total payoff to equity holders is the sum of cash flows from assets in place and the payoff from the contractual fulfillment to customers, less the production cost, the operational hedging cost and the debt repayment, provided that the firm does not default on its debt in the interim. The market value of equity is therefore given as:

$$E = \int_{u_F}^{\infty} \Big[u - u_F + p\left[(1-\delta(u))I + i\right] + x_2\Big] g(u)du \ , \tag{2.8}$$

where u_F is given in (2.2). $(u - u_F)$ is the amount of cash left in the firm after debt F is repaid, and $p\left[(1-\delta(u))I + i\right] + x_2$ is period-2 cash flow, conditional on the firm not defaulting in the interim.

Equity holders choose the level of operational hedging i to maximize equity value E in

[11] It is straightforward to consider hedging being undertaken by a manager who maximizes equity value net of personal costs arising from firm's bankruptcy (see, for example, Gilson (1989)). This extension is available upon request.

(2.8), which yields the following first-order condition:

$$p - K'(I + i) = V(u_F, i)h(u_F)K'(I + i) \ , \tag{2.9}$$

where $V(u_F, i) \equiv p\left[(1 - \delta(u_F))I + i\right] + x_2$ is the firm's date-2 franchise value at the financial default boundary. On the one hand, a marginal increase in operational hedging will yield a marginal profit equal to its markup $p - K'(I + i)$. On the other hand, a marginal increases in operational hedging also increases the expected cost of financial default, which is the product of three terms on the right-hand side of Equation (2.9): the first term is the loss of date-2 franchise value if financial default occurs; the second term is the hazard rate of a financial default; and, the last term is the marginal effect of additional operational hedging on the financial default boundary u_F. The first-order condition says that the firm chooses the optimal hedging policy i^* such that the markup is equal to the marginal increase of the expected financial default cost.

Since u is exponentially distributed on $[0, \infty)$ with $g(u) = \alpha e^{-\alpha u}$ and $h(u) = \alpha$, the first-order condition (2.9) simplifies to

$$p - K'(I + i) = V(u_F, i)\alpha K'(I + i) \ . \tag{2.10}$$

Define i^* is the firm'optimal hedging policy that satisfies (2.10). The following assumption guarantees that a positive interior solution i^* exists and $D(i^*, \bar{F}) > 0$ for sufficiently large $\bar{F}$:[12]

Assumption 2.2. $p - K'(I) > (pI + x_2)\alpha K'(I)$.

Appendix IA.4 proves the following lemma.

Lemma 2.1. *If Assumption 2.2 holds and $\bar{F}$ is sufficiently large, then the first-order condition* (2.10) *admits a positive interior solution i^* is a uniquely solution that maximizes E subject to $D(i, \bar{F}) > 0$.*

[12]We assume that initial cash holdings are high enough to avoid the corner solution, i.e., the production cost of I units of goods and the chosen operational hedging level i, is less than $x_0 + x_1$.

Lemma 2.2, also proved in Appendix IA.4, states that the optimal optimal operational hedging policy decreases in the firm's net debt level maturing in the interim:

Lemma 2.2. *When $\bar{F}$ is sufficiently high such that $D(i^*, \bar{F}) > 0$, the equilibrium operational hedging policy i^* decreases in the firm's net debt level $\bar{F}$.*

2.5 Optimal hedging policy when $u_F < u_O$

We now turn to the case in which the firm's inherited debt level is sufficiently low such that the financial default boundary is always below the operational default boundary. In this case, the operational default boundary enters the equity value function. The equity value is E given in (2.8), minus the expected cost proportional to unlevered firm value at date-2, λx_2, if the firm defaults on its supplier contract, provided that the firm does not default on its debt in the interim. The equity value is therefore,

$$\hat{E} = E - \int_{u_F}^{u_O} \lambda x_2 g(u) du \ , \tag{2.11}$$

Equity holders choose the optimal level of operational hedging i to maximize $\hat{E}$, which yields the following first-order condition:

$$p - K'(I+i) = [V(u_F, i) - \lambda x_2] h(u_F) K'(I+i) + \frac{\lambda x_2 g(u_O)}{[1 - G(u_F)] I \delta'(u_O)} \ . \tag{2.12}$$

Define $\hat{i}^*$ as the firm's optimal hedging policy that satisfies (2.12). Similar to the case in which $u_F > u_O$, a marginal increase in operational hedging will yield a marginal profit equal to its markup $p - K'(I+i)$. However, the effect of a marginal increase in i on the firm's expected loss from operational default and financial default is opposite. On the one hand, a marginal increases in operational hedging increase the expected cost of financial default by increasing the financial default boundary u_F.[13] On the other hand, a marginal increase in operational hedging decreases the expected cost of operational default since it reduces

[13]Notice that the loss conditional on a financial default is reduced by λx_2. This is because the firm has already lost λx_2 due to operational default when it declares financial default.

the operational default boundary u_O, which is captured by the last term of the first-order condition (2.12). Therefore, the first-order condition (2.12) says that the firm chooses the optimal hedging policy $\hat{i}^*$ such that the marginal profit ("markup") is equal to the marginal increase of the expected financial default cost net of the marginal decrease of the expected operational default cost. We show in Appendix IA.5 that

Lemma 2.3. *If the production commitment I is sufficiently high and $\frac{K'(I+\bar{i})}{I}$ is sufficiently low, then $\hat{i}^*$ that satisfies* (2.12) *uniquely maximizes $\hat{E}$.*

Intuitively, the condition that I is sufficiently high means that the supply contract value is not trivial. The condition that $\frac{K'(I+\bar{i})}{I}$ is sufficiently low means that the firm's marginal production cost does not increase too fast as the production quantity increases. This condition makes sure that the firm has enough flexibility to do the operational hedging even if the production quantity is high.

When the firm's inherited net debt $\bar{F}$ is sufficiently low such that the operational default boundary u_O always dominates the financial default boundary u_F, operational default risk is main concern of equity holders. Thus, the firm will invest more on operational hedging, i.e., $\hat{i}^* > i^*$. The following lemma, proved in Appendix IA.5 confirms this intuition:

Lemma 2.4. *If Lemma 2.3 holds, the operational hedging policy $\hat{i}^*$ that satisfies Equation* (2.12) *is higher than the operational hedging policy i^* that satisfies Equation* (2.9)*, i.e., $\hat{i}^* > i^*$.*

Similar to the $u_F > u_O$ case, Appendix IA.5 derives that when u_F is always less than u_F, the firm's optimal operational hedging policy $\hat{i}^*$ decreases in its inherited net debt level:

Lemma 2.5. *If Lemma 2.3 holds, the equilibrium operational hedging policy $\hat{i}^*$ decreases in the firm's net debt level $\bar{F}$.*

2.6 Optimal hedging policy and net debt $\bar{F}$

We now formally characterize the correlation between the firm's optimal operational hedging policy and its inherited net debt level $\bar{F}$.

Let $\bar{F}_{fb}$ is such that $\bar{F}_{fb} + K(I + \bar{i}) = 0$, i.e., $\bar{F}_{fb}$ is the maximal net debt level such that the firm is able to pay back the debt at date-1 when it chooses the maximal optimal hedging policy $\bar{i}$ that maximizes the unlevered firm value, as derived in Section 2.3.1. When $\bar{F} \leq \bar{F}_{fb}$, short-term debt is riskless and the firm chooses the optimal hedging policy as if the short-term debt level is zero. Recall that $D = u_F - u_O$ is defined in Equation (2.4). We introduce $D^*(\bar{F}) \equiv D(i^*(\bar{F}), \bar{F})$ and $\hat{D}^*(\bar{F}) \equiv D(\hat{i}^*(\bar{F}), \bar{F})$, i.e., D^* and $\hat{D}^*$ are the differences between financial default boundary u_F and operational default boundary u_O when the firm chooses the operational hedging policy i^* and $\hat{i}^*$ respectively. Define $\bar{F}_0$ to be such that $\hat{D}^*(\bar{F}_0) = 0$ and $\bar{F}_1$ such that $D^*(\bar{F}_1) = 0$. Appendix IA.6 shows that $\bar{F}_0$ and $\bar{F}_1$ exist and are unique with $\bar{F}_0 < \bar{F}_1$. $\hat{D}^* < 0$ if $\bar{F} < \bar{F}_0$ and $\hat{D}^* > 0$ if $\bar{F} > \bar{F}_0$. Similarly, $D^* < 0$ if $\bar{F} < \bar{F}_1$; and, $D^* > 0$ if $\bar{F} > \bar{F}_1$. The following proposition formalizes this relationship between the firm's optimal operational hedging policy and its net debt level maturing at date-1:

Proposition 2.1. *If Lemma 2.3 holds, then*

I. If $0 \leq \bar{F} \leq \bar{F}_{fb}$, the firm's optimal operational hedging policy is $\bar{i}$.

II. If $\bar{F}_{fb} < \bar{F} \leq \bar{F}_0$, the firm's optimal operational hedging policy is $\hat{i}^*$.

III. If $\bar{F}_0 < \bar{F} < \bar{F}_1$, the firm's optimal operational hedging policy is $\tilde{i}$ such that $u_F = u_O$.

IV. If $\bar{F} \geq \bar{F}_1$, the firm's optimal operational hedging policy is i^*.

The next proposition states the main results of in our paper: The firm faces a tradeoff between saving cash (financial hedging) and investment in operational hedging. When the firm is more financially leveraged in the interim, i.e., having higher net debt levels $\bar{F}$ maturing at date-1, financial hedging motive dominates the operational hedging motive; the firm cuts investment in operational hedging to conserve more cash, in order to better weather the financial default. As a result, the optimal operational hedging, denoted by i^{**}, is lower.

Proposition 2.2. *When $\bar{F} > \bar{F}_{fb}$, the firm's optimal operational hedging policy i^{**} decreases in net debt $\bar{F}$.*

3. Model extensions

3.1 The effect of partial pledgeability

In our base-case model of Section 2, the firm has no access to external financing. In this subsection, we extend the model to consider the effect of partial pledgeability ("PP") of cash flows from supplier contract settlement. We use subscript PP to denote respective quantities for this extension.

Suppose that at $t = 1$ the firm can use a fraction τ of its proceeds from date-2 supplier contract settlement (which is $\tau p[(1 - \delta(u))I + i]$) as collateral for new financing, where $0 \leq \tau \leq 1$. Here, $\tau = 0$ corresponds to our base case of extreme financing frictions, when the firm cannot raise any external financing against its future cash flow, whereas $\tau = 1$ implies frictionless access to external capital with payment backed by future cash flow. In practice, τ can also represent the ease of access to cash flow financing.

Conditional on survival, raising new financing at $t = 1$ in this setting is value-neutral. Therefore, we can assume without loss of generality that the firm always raises the amount equal to the cash shortfall when the cash flow shock hits the financial default boundary $u_{F,PP}$. Thus, cash available for debt service at date 1 is $x_0 - K(I+i) + x_1 + \tau p[(1-\delta(u_{F,PP}))I + i]$, which is the sum of the cash reserve $x_0 - K(I + i)$, the random cash flow $x_1 = \bar{x}_1 + u$, and the newly borrowed amount $\tau p[(1-\delta(u_{F,PP}))I+i]$. While the operational default boundary u_O is the same as the base case, the financial default boundary is now given as:

$$u_{F,PP} = \bar{F} + K(I + i) - \tau p[(1 - \delta(u_{F,PP}))I + i] \ . \tag{3.1}$$

In turn, the value of equity when $u_{F,PP} > u_O$ can be written as

$$E_{PP} = \int_{u_{F,PP}}^{\infty} \Big[(u - u_{F,PP}) + (1 - \tau)p[(1 - \delta(u_{F,PP}))I + i] + x_2\Big] g(u)du \ . \tag{3.2}$$

The partial pledgeability case can be solved in an analogues manner as the zero pledgeability case. We define $\hat{i}^*_{PP}$ as the optimal hedging policy that maximizes the equity value when $u_{F,PP} < u_O$; $\tilde{i}_{PP}$ as the optimal hedging policy that equalizes the operational and financial default boundaries $u_O(\tilde{i}_{PP}) = u_{F,PP}(\tilde{i}_{PP}, \bar{F})$; and, i^*_{PP} as the optimal hedging policy that maximizes the equity value when $u_{F,PP} > u_O$. Specifically, i^*_{PP} and $\hat{i}^*_{PP}$ are given respectively by the following first-order conditions:

$$p - K'(I + i^*_{PP}) = V(u_{F,PP}, i^*_{PP})\; h(u_{F,PP})\; \frac{[K'(I + i^*_{PP}) - \tau p]}{[1 - \tau p \delta'(u_{F,PP}) I]} \;, \tag{3.3}$$

$$\begin{aligned} p - K'(I + \hat{i}^*_{PP}) = &\left[V(u_{F,PP}, \hat{i}^*_{PP}) - \lambda x_2 \right]\; h(u_{F,PP})\; \frac{[K'(I + \hat{i}^*_{PP}) - \tau p]}{[1 - \tau p \delta'(u_{F,PP}) I]} \\ &+ \frac{\lambda x_2 g(u_O)}{[1 - G(u_{F,PP})] I \delta'(u_O)} \;. \end{aligned} \tag{3.4}$$

As long as τ is sufficiently low, the optimal hedging policy is of the same form as that in the baseline case. Consequently, the optimal operational hedging, denoted by i^{**}_{PP}, is lower when the inherited net debt level $\bar{F}$ is higher.

Define $\bar{F}_{fb,PP}$ to be such that

$$\bar{F}_{fb,PP} + K(I + \bar{i}_{PP}) = \tau * p * \bar{i}_{PP} \;. \tag{3.5}$$

In other words, $\bar{F}_{fb,PP}$ is the maximal net debt level such that the firm is able to pay back the debt at date-1 even if the production shock u is severe enough to obliterate the entire production capacity I. $\bar{F}_{0,PP}$ and $\bar{F}_{1,PP}$ are defined analogously to the respective thresholds in Proposition 2.1: $\bar{F}_{0,PP}$ is such that $u_{F,PP}(\hat{i}^*_{PP}, \bar{F}_{0,PP}) = u_O(\hat{i}^*_{PP})$; $\bar{F}_{1,PP}$ is such that $u_{F,PP}(i^*_{PP}, \bar{F}_{1,PP}) = u_O(i^*_{PP})$. The following proposition characterizes the firm's optimal hedging policy as a function of $\bar{F}$ when the pledgeability is imperfect, i.e., $\tau < \bar{\tau} < 1$:[14]

Proposition 3.1. *There exists $\bar{\tau} < 1$ such that if $\tau < \bar{\tau}$, then*

I. If $0 \le \bar{F} \le \bar{F}_{fb,PP}$, the firm's optimal operational hedging policy is $\bar{i}$.

II. If $\bar{F}_{fb,PP} < \bar{F} \le \bar{F}_{0,PP}$, the firm's optimal operational hedging policy is $\hat{i}^*_{PP}$.

[14] The proofs of Proposition 3.1 and Proposition 3.2 are similar to the base case although the algebra is much more involved. The proofs are available upon request.

III. If $\bar{F}_{0,PP} < \bar{F} < \bar{F}_{1.PP}$, the firm's optimal operational hedging policy is $\tilde{i}_{PP}$ such that $u_{F,PP} = u_O$.

IV. If $\bar{F} \geq \bar{F}_{1,PP}$, the firm's optimal operational hedging policy is i^*_{PP}.

Proposition 3.2. *If $\tau < \bar{\tau}$ and $\bar{F} > \bar{F}_{fb,PP}$, the firm's optimal operational hedging policy i^{**} decreases in $\bar{F}$.*

When $\tau = 0$, the general case is reduced to the zero-pledgeability case we just presented in Section 2. Since all the quantities are continuous in τ, Proposition 3.1 and Proposition 3.2 hold for small enough τ, i.e., $\tau \in [0, \bar{\tau}]$.

3.2 Operational spread and credit spread

Consistent with Acharya et al. (2012), the credit spread is defined by the ratio between the face value of debt F and the market value of debt D minus 1. The market value of debt is given as:

$$D = F - \int_0^{u_F} \left[u_F - u - \tau p \left(\delta(u_F) - \delta(u)\right) I\right] g(u) du \; . \tag{3.6}$$

The second term of Equation (3.6) is the expected bankruptcy cost. Then, the credit spread s is

$$s = \frac{F}{D} - 1 \; . \tag{3.7}$$

The operational spread is the markup, $p - K'(I+i)$. Our model predicts that the operational spread and credit spread are positively correlated. To see this, note that $\frac{di^{**}}{dcs} = \frac{\partial i^{**}}{\partial F}\frac{dF}{ds} = \frac{\partial i^{**}}{\partial F} D$. By Proposition 2.2, the above quantity is smaller than zero, meaning that the optimal operational hedging level i^{**} decreases in the credit spread s. The operational spread also decreases in the operational hedging level i. Thus, we have the following proposition:

Proposition 3.3. *In equilibrium, operational spread and credit spread are positively correlated.*

3.3 Debt maturity

So far, we assume that the firm's existing debt matures at date-1, before the supplier contract delivery. What happens if the debt matures at date-2, at the same date as the contract delivery? If the debt maturity date is aligned with the delivery date of the supplier contract, then the firm can use its entire cash flow from its supplier contract settlement to pay off its debt. Thus, the optimal operational hedging policy in the "long-term" debt case is the same as the case of perfect pledgeability ($\tau = 1$). In fact, although we interpret τ as the pledgeability of the cash flow from the supplier contract, we can also treat $(1 - \tau)$ as the proportion of the firm's debt that matures before the contract delivery, i.e., the mismatch between the firm's debt maturity structure and the duration of its operational cash flows.

3.4 Supply chain diversification

We can modify our model slightly to accommodate the case in which the firm hedges against the operational default risk by choosing multiple suppliers instead of choosing spare production capacity or excess inventory. Suppose that the production function becomes $K = K(I, n)$, in which $n \geq \underline{n}$ denotes the measure of suppliers that the firm chooses to enlist in the production process, and $\underline{n}$ denotes the minimal measure of suppliers that the firm needs to keep the production running.[15] We assume that it is more costly if the firm chooses a more diversified supply chain, i.e., n being large. Mathematically, it means that the first- and second-order partial derivatives of K with respect to n are both positive: $K_n(I, n) > 0$ and $K_{nn}(I, n) > 0$. We assume that the production loss function $\delta(u, n)$ depends on both the production shock u and the measure of suppliers n. Consistent with the baseline model, $\delta(u, n)$ is decreasing and convex in both u and n with continuous and finite first- and second-order derivatives, $\delta_u(u, n) < 0$, $\delta_n(u, n) < 0$, $\delta_{uu}(u, n) > 0$ and $\delta_{nn}(u, n) > 0$. In addition, we assume that the cross-partial derivative of $\delta(u, n)$, $\delta_{un}(u, n) < 0$.

In this setting, the operational default threshold u_O is such that $\delta(u_O, n) = 0$. Then

[15] We assume that n represents the measure, instead of number of suppliers, in order to use the first-order conditions, consistent with our baseline model.

$\frac{\partial u_O}{\partial n} = -\frac{\delta_n(u_O,n)}{\delta_u(u_O,n)} < 0$. It can be verified that the second-order derivative of u_O with respect to n is greater than zero, which is the same as the baseline case. In this setting, our previous arguments still go through. In particular, operational hedging measured as supply chain diversification (n) is decreasing in firm's financial leverage and credit risk.

4. Numerical analysis

This section presents comparative statics from the model. We illustrate the correlations between the optimal hedging policy i^{**} and debt F maturing at date-1, as well as between the credit spread and operational spread, as implied by the model solutions in Section 2.[16]

Throughout this section, we focus on the generalized version of the model in Section 3.1 with pledgeability level $\tau \in [0, 1]$. As mentioned in Section 2.1, the cash flow shock u follows an exponential distribution with rate parameter $\alpha = 0.05$, i.e., the probability density function of u, $g(u) = 0.05e^{-0.05u}$. The production loss function is assumed to be $\delta(u) = e^{-u}$. Consistent with neoclassic investment literature (Bolton et al., 2011), we assume that a quadratic production cost function $K(I + i) = \kappa(I + i)^2$, in which $\kappa = 0.1$. All parameter values are in Table 1.

[INSERT Table 1.]

Figure 1 presents the firm's optimal operational hedging policies i^{**} given different debt levels F. The blue, red and yellow lines represent the cases of low ($\tau = 0$), intermediate ($\tau = 0.4$) and high pledgeability ($\tau = 0.8$) cases, respectively. In all three cases, the optimal hedging policy i^{**} is flat when the debt level F is low. This corresponds to the scenario I of Proposition 3.1: debt does not affect the firm's optimal hedging policy when the debt level is sufficiently low, i.e., the debt is guaranteed to be paid off at date-1 regardless of the date-1 production shock levels. As F increases, i^{**} exhibits a negative correlation with the debt

[16] Our model treats the debt level (F) as a model primitive. In untabulated numerical analyses, we introduce the tax benefit of debt and solve for the optimal capital structure. The results are available upon request.

level maturing at date-1. Moreover, the negative slope is steeper and holds for a wider range of debt levels F the lower is the pledgeability τ. Overall, the optimal operational hedging policy decreases in the amount of debt maturing in the interim, especially if the firm faces difficulty in raising external funds, i.e., has a low pledgeability τ.[17]

[INSERT Figure 1.]

In what follows, we plot the firm's credit spread against its operational spread, i.e., the markup $p - K'(I + i)$. Proposition 3.3 is confirmed in Figure 2: At the optimal hedging policy given the debt level F, the credit spread and operational spread are positively correlated. This positive relationship is stronger when the firm's pledgeability τ is lower. This is consistent with the novel implication of our model: when the firm's credit spread is higher, the firm cuts the operational hedging activity by a larger extent to save more cash at date-0 and better hedge against the financial default risk.

[INSERT Figure 2.]

5. Empirical analysis

5.1 An overview of empirical tests

Our model shows that operational hedging declines with the amount of the firm's credit risk, captured by its credit spread. A higher credit risk induces the firm to allocate more resources to avert financial default and spend less on operational hedging, which result in lower costs and higher price-unit cost margin or operational spread. Our model also predicts that higher existing leverage, especially shorter-term leverage that imposes a liquidity requirement, induces the firm to allocate resources to avoid financial default while spending less on operational hedging, which again raises the operational. We further show that the

[17] From Equation (3.5), $\bar{F}_{fb}$ increases in the pledgeability τ. Thus the F-region in which debt level does not affect the optimal hedging policy increases with τ.

positive relation between operational spread and both leverage and credit risk should be stronger when the firm face pledgeability constraints.

We test these implications as follows. First, we document that the markup, our measure of operational spread, is negatively correlated with indicators associated with operational hedging, as we predict. Specifically, we find that markup declines in the level of inventory whose hoarding indicates the propensity of the firm to engage in operational hedging, and it also declines in measures of supply chain diversification. This initial test suggests that the markup can be taken as a summary measure of the extent of operational hedging that the firm engages in.

We then examine whether measures of leverage and credit risk affect the operational spread in the way predicted by our model. In particular, we test whether markup is an increasing function of credit risk and leverage, especially the portion of debt that matures within two years. This breakdown is particularly important because our model focuses on the consequences for operational hedging of the immediate needs to avoid financial default, which is especially intense when debt is due for redemption. Notably, the maturity time of the short-term portion of the long-term debt has been determined in the past when the long-term debt was issued and thus it is exogenous to the current state of the firm and its current production plans. We propose that the need to avoid financial default induces the form to reduce operational hedging, leading to a wider markup. At the same time, there should be a muted effect of the long-term debt on operational hedging and on markup.

Next, we test the prediction that if firms need to hoard liquidity to avert financial default, credit risk has a negative effect on operational hedging. Our first strategy directly uses liquidity hoarding to identify firms that are likely to face a stronger trade-off between credit risk and operational hedging. Specifically, we sort firms by their cash holdings (after controlling for other motives for holding cash) since the level of cash held by firms reflects managerial private information about cash needs and about potential risk of financial default. Thus, higher cash holding indicates a greater managerial concern about financial default, which by our model induces shifting resources away from operational hedging. This strategy follows the proposition in Acharya et al. (2012, p.3603) "firms' cash holdings respond endogenously to the possibility of a liquidity shortage, which in the presence of restrictions on external financing can trigger costly default." That is, cash accumulation by managers may indicate their perception of a difficulty in fund raising to mitigate the risk of default. We implement this measure of perceived restricted financing by using the level of residual cash after controlling for basic determinants of cash holdings such as cash flow uncertainty (Riddick and Whited, 2009) and industry characteristics. We sort firms by the excess cash held after controlling for these factors into high-cash and low-cash groups. As two robustness checks, we also eliminate data on the largest firms, which are likely to hold cash for tax reasons prior to the change in the US tax code in 2018, and firms with positive pre-tax foreign income.

In addition, we use two time-series variations in financing conditions to identify situations in which credit risk should have a stronger effect on operational hedging and thus markup. In the first test, we find that the positive relationship between markup and leverage is more prominent during recession periods, designated by NBER. Moreover, we find that inventory drops more drastically during the recession for firms entering recession in more precarious liquidity positions. In the second test, we also analyze the negative impact of the subprime mortgage crisis of 2008 on lenders' abilities to extend credit to borrowers, following Chodorow-Reich (2014). Specifically, we test whether exposed firms whose credit risk and leverage were higher prior to the crisis reduced operational hedging by more than less exposed firms, leading to a higher markup. This test uses time series variation in financing conditions to measure the key tension between operational hedging and liquidity hoarding emphasized in our paper, and it helps address concerns about the endogeneity of leverage; studies of the impact of the financial crisis show that pre-crisis leverage is an important determinant of the post-crisis real effects through a liquidity channel (e.g., Giroud and Mueller, 2016).

5.2 Data and empirical definition

We employ quarterly data from 1971 to April 2020, a span of 197 quarters, from Compustat. We exclude firms in the financial industries (SIC codes 6000-6999) and utility industries (SIC codes 4900-4949), and firms involved in major mergers (Compustat footnote code AB). We include firm-quarter observations with market capitalization greater than \$10 million and quarterly sales more than \$1 million at the beginning of the quarter, inflation adjusted to 2019. Our sample includes $18,752$ firms with an average asset value of \$2.9 billion dollars (inflation adjusted to the end of 2019). Altogether we have $599,677$ firm-quarters.

5.2.1 Variable definitions

Our dependent variable is the operational spreads or Markup, which we define empirically as sales ($SALEQ$) minus cost of goods sold ($COGSQ$) divided by sales. Thus, $Markup = 1 - COGSQ/SALESQ$, that is, the negative of cost of goods sold scaled by sales. This measure of the price-unit cost spread proxies for our model's marginal cost of production of the contracted output quantity, which we use the measure the effect of operational hedging cost. This measure of the price-unit cost spread proxies for our model's marginal cost of production of the contracted output quantity, which we use the measure the effect of operational hedging cost. Our independent variables of interest are proxies for the firm's ability to pay off its debt liabilities. Our independent variables of interest are proxies for the firm's ability to pay off its debt liabilities. We use three measures: Z-score (e.g., Altman, 2013)[18] and financial leverage, the financial debt ($DLTTQ + DLCQ$) divided by total assets (ATQ). We use the negative value of Z-score so that a higher value means that the firm has greater financial risk. In addition, we use Long-term debt maturing in the next 2 years (($DD1 + DD2$) according to the most recent fiscal year-end/total assets), controlling for the Remaining long-term leverage ($DLTTQ - DD2$) divided by total assets.[19] We include variables to control for the firm's investment needs and its debt capacity. We control for firm size by including total assets in logarithms. To control for the firm's investment opportunities we include Tobin's Q, the sum of common shares outstanding ($CHOQ$) multiplied by the

[18]Z-score is computed using the following formula: Z-score = 1.2×(current assets ($ACTQ$)−current liabilities ($LCTQ$))/assets+1.4× retained earnings (REQ)/assets+3.3×EBIT ($OIBDPQ$)/assets+0.6×market value of equity ($PRCCQ \times CSHOQ + PSTKQ + DVPQ$)/total liabilities ($LTQ$)+1.0×sales/assets. We use $OIBDP$ instead of $EBIT$ because the latter is not available in Compustat quarterly data.

[19]In COMPUSTAT, $DD1$ is included in $DLCQ$.

stock price at the close of the fiscal quarter ($PRCCQ$), preferred stock value ($PSTKQ$) plus dividends on preferred stock ($DVPQ$), and liabilities (LTQ), scaled by total assets, to control for the firm's potential investment (e.g., Covas and Den Haan, 2011). To control for the firm's debt capacity, we include cash holdings ($CHEQ$), cash flow ($IBQ + DPQ$) and tangible assets ($PPENTQ$), all scaled by total assets. We use three variables to control for market power, given that markup is associated with monopoly power (Lerner, 1934) and with inventory behavior (e.g., Amihud and Medenelson, 1989). One variable is a dummy variable for the top 3 industry seller, which equal one if the firm's sales ranks among the top three sellers in the industry in a given quarter, using Fama and French's 38 industries, and zero otherwise. The second variable is the firm's sales/industry sales, and the third is Herfindahl's index for the industry.

We use variables that are associated with operational hedging. The disruptions of supply chains during the 2020 Covid-19 pandemic highlighted the importance of a new form of operational hedging, supply chain diversification. Indeed our model accommodates supply chain diversification as a measure of operational hedging (see Section 3.4). We thus create operational hedging measures using information on firms' supply chains using information from the Factset Revere relationship database.[20] It contains a comprehensive relationship-level data between firms, starting from April 2003. An observation in this database is the relationship between two firms with information about the identities of the related parties, the start and end date of the relationship, the type of the relationship (e.g., competitor, supplier, customer, partner, etc.), and importantly, the firms' geographic origins.

We aggregate the relationship-level data to firm-quarter level and calculate three measures of supply chain diversification for each firm in each quarter: (i.) ln(1+number of suppliers); (ii.) ln(1+number of supplier regions), where supplier regions are country and state/province combination; (iii.) ln(1+number of out-of-region suppliers), that is, suppliers that are not from the firm's region. We merge the supply-chain data to our main sample, yielding a total of $151,985$ firm-quarter observations covering $6,204$ firms, from mid-2003 to

[20]Factset Revere has much better coverage of supply chain information than the COMPUSTAT segment data and used by some studies about supply chain (e.g., Ding et al., 2020).

the first quarter of 2020. The median firm has 4 suppliers from 3 regions in a given quarter, out of which 3 suppliers are not from the same region as the firm. We create two composite measures of supply chain diversification using the three aforementioned individual measures.

(1) Supply chain diversification index, the first principal component score from a principal component analysis using three individual measures: supply chain diversification index = 0.5745×ln(1+number of suppliers)+0.5796×ln(1+number of supplier regions)+0.5779× ln(1+number of out-of-region suppliers).[21] A higher supply chain diversification index indicates a more diversified supply chain network.

(2) Supply chain diversification ranking, negative value of the average across the three supply chain variables of the ranking of the firm-quarter ranking for each of the individual measure. The ranking for each of the three series is scaled by the number of non-missing variables. A larger value of supply chain diversification ranking indicates a more diversified supply chain network.

In Appendix IA.2, we empirically validate that our measures of supply chain diversification are indeed a means to hedge against negative industry and economy-wide shocks: the stock returns of firms with more diversified supply chains, according to our measures, are less exposed to negative industry stock returns and negative changes in industrial productions of the economy.

Finally, our analysis includes natural logarithm of one plus inventory ($INVTQ$) divided by sales as an indicator of operational hedging. Table 2 presents summary statistics of the variables in our study. All continuous variables in our analysis are winsorized at the 1% and 99% tails.

[INSERT Table 2.]

[21] The first principal component explains 97% of the sample variance.

5.3 The relationship between markup and operational hedging

Our model implies that higher operational hedging activities translates into lower markup through increased marginal production cost. We test whether this implication is supported by the evidence. We estimate the following model using data for firm j in quarter t,

$$Y_{j,t} = \sum_k \beta_k X_{k,j,t-1} + \sum_m \beta_m Control\ variables_{m,j,t-1} + firm\ FE + year - quarter\ FE \quad (5.1)$$

The dependent variable $Y_{j,t}$ is $Markup_{j,t}$ and $X_{k,j,t-1}$ are the explanatory variables that we focus on which include either of the three supply chain diversification measures and $Inventory/sales$. Inventory serves here as an indicator of the firm's propensity to expend resources for the purpose of operational hedging, consistent with our model in which the firm produces a higher output than contracted for as a means to avert the cost of a shortfall on its contract with customers in case of a negative shock to output. The control variables are Tobin's Q, log assets, cash holdings, cash flow, asset tangibility, and the three variables that measure market power, which is known to affect markup. The model includes firm and year-quarter fixed effects with standard errors clustered by firm and by year-quarter.

[INSERT Table 3.]

By the results in Table 3, markup is negatively affected by indicators of operational hedging. That is, higher values of the proxies for operational hedging raise the firm's unit cost, which leads to a lower Markup. Markup is significantly lower when the firm spends more on supply chain diversification and when it increases inventory. All three measures of supply chain diversification indicate that. markup is declining in the PCA index of the three supply chain diversification variables; it is declining in the index of standardized average of these variables; and it is increasing in the ordinal index of average ranking by which a lower number means a higher ranking. To illustrate the economic significance of the estimated effect, by the estimation in Column (2), a rise of one place in the ranking of supply chain diversification, which means a decline by one unit, increases *Markup* by 0.04 which is 12% of its mean. By the estimation in column (1), one standard deviation increase in Supply chain diversification index will lower markup by 0.01, and one standard deviation increase in inventory-sales ratio lowers markup by 0.02. Overall, the results suggest that markup is a reasonable summary of firms' operational hedging activities, as our model implies.[22]

5.4 Baseline results

We estimate the main prediction of our model of the tradeoff between allocating funds to avert financial default and spending on operational hedging. We propose that firms in financial distress and with high leverage will reduce spending on operational hedging, resulting in a higher operation spread which we proxy by markup. We estimate Model (5.1) where $Y_{j,t} = Markup_{j,t}$ and the explanatory variables $X_{k,j,t-1}$ include the variables that indicate he firm's credit risks: -(z-score), since the credit spread increases in this variable, and leverage. As before, the control variables are Tobin's Q, cash holdings, log assets, cash flow, asset tangibility, and the three measures of market power, as well as firm and year-quarter fixed effects.[23]

[INSERT Table 4.]

Table 4, Panel A, presents our baseline results. As predicted in Proposition 3.2 of our model, the operational spread, measured by Markup, is positively affected by the firm's credit risks, measured by either the credit spread or the leverage ratio. That is, faced with a higher likelihood of financial default and a greater need for resources for financial hedging, firms reduce their expenses on operational hedging. This leads to a decline in their unit cost and then Markup increases.

To gauge the economic significance of the effect, one standard deviation increase in the firm's negative z-score raises the firm's markup by 0.05 standard deviation, or 7% of the sample median markup. And, one standard deviation increase in leverage results in 0.02 standard deviation increase in markup.

[22] Using individual supply chain diversification measures instead of composite measures yields qualitatively similar results.

[23] Our main results are qualitatively similar if we include firm and industry $\times$ year-quarter fixed effects.

In our theoretical model, it is the liquidity need to avoid financial default that presses the firm to divert resources from operation hedging. This is because the firm's existing debt matures before the contracted delivery date of its output. This maturity mismatch between debt obligations and operational cash flow contributes to the tension between financial hedging and operational hedging. It follows that short-term leverage should have a larger impact on operational hedging or markup than the impact of long-term leverage.

We test this hypothesis by studying the effect of the portion of debt which matures in the coming two years. Importantly, the short-term part of the long-term debt had its maturity determined in the past when the debt was issued. Thus it is not determined simultaneously with operational hedging policies in response to the current state of the firm and its environment.

The results in column (4) of Table 4, Panel A, show that the effect on markup of the short-term debt — the part of long-term that matures in the next two years — is more than twice as large as that of the remaining long-term debt maturing in more than two years, with the difference between the coefficients being statistically significant at the 0.05 level.[24] The result supports our theoretical prediction that it is the pressing liquidity need that induces firms to shift funds from operational hedging to the accommodation of the need to avoid financial default. In column (5), we include -(z-score) together with the two leverage variables, the short term and long-term part of leverage. We find that the coefficients of both -(z-score) and the short-term part of the long-term debt are positive and significant, as predicted by our model, while the coefficient of the remaining long-term debt is positive but smaller in magnitude and statistically insignificant.

Figure 3 presents binned scatter plots of the relationship between operational spread and either -(z-score) or leverage. Following the methodology of Rampini et al. (2014),[25] we first residualize *Markup*, -(z-score) and leverage with respect to the baseline control variables (including the firm and year fixed effects), as in Table 4. We then add back the unconditional

[24] In untabulated result, we also test for the significance of the difference between coefficients on long-term debt maturing in the next two years and remaining long-term leverage, the difference is 0.036 with t-statistic equal to 2.28.

[25] We thank Raj Chetty for making the relevant STATA program available.

mean of the respective variables in the estimation sample to facilitate interpretation of the scale. Finally we divide the x-axis variable into twenty equal-sized groups (vingtiles) and plot the means of the y-variable within each bin against the mean value of x-variable within each bin. Figure 3a and Figure 3b correspond to the estimations in columns (1) and (2) of Table 4, Panel A, respectively. We see that the markup monotonically increases with one-period lagged values of both -(z-score) and leverage. Notably, the monotonic relationships between the firm's credit risk and markup across all the bins shows that that our results are not driven by extreme observations.

In our model, the firm's Markup rises in the firm's leverage or credit spread because higher level of these variables means that the firm needs resources to avert financial default and thus lower expenses on operational hedging. This lowers the firm's unit cost and raises its markup. Recently, Gilchrist et al. (2017) propose that levered firms that face financial constraint raise prices when faced with low liquidity, which would raise the firm's markup. This is because a negative liquidity shock induces firms to reduce their investment in expanding their customer base via price reductions. Following a negative liquidity shock firms become more myopic and raise prices to increase current profitability while sacrificing their market share. This tradeoff is relevant for firms operating in a monopolistic competition with a sticky customer base.

We test whether our results are affected by the firm's market power. Our control variables include three measures of market power: a dummy variable for top 3 industry seller, which equal one if the firm's sales ranks among the top three sellers in the industry in a given quarter, using Fama and French's 38 industries, and zero otherwise. The second variable is the firm's sales/industry sales, and the third is Herfindahl index for the industry. Denote these variables MP_1, MP_2 and MP_3, respectively. We now add the interaction terms, -(z-score) $\times$ MP_k and leverage $\times$ MP_k, for $k = 1, 2, 3$. By Gilchrist et al. (2017), if greater liquidity needs induce firms to raise prices, our estimated positive effect of -(z-score) and leverage on Markup should be higher for firms that have greater market power.

We add these interaction variables to the models in Columns (1) and (2) in Table 4.

Importantly, in all estimations, the coefficients of -(z-score) and leverage remain positive and highly significant (at $p < 0.01$). This means that our model's prediction on the positive effect of the firm's liquidity need on Markup remains strongly supported. (The tabulated results are available upon request.)

Overall, we do not find evidence that financially distressed firms with market power raise their markups possibly by raising product prices, as suggested by Gilchrist et al. (2017). The effect of firms' credit risk on their markup strategies are at least partially through unit cost, as suggested by our model.

We now turn to test our prediction that the tradeoff between operational hedging and financial hedging is stronger when pledgeability is low, indicated by a value of τ, which indicates difficulty in raising funds. Empirically, we expect that when firms foresee a problem in raising funds to avert financial default, they more aggressively shift resources from operational hedging to financial hedging. Then there is a stronger effect on markup of -(z-score) and of leverage, particularly the portion of it that is due within two years. We measure the financial strain of the firm by the level of its cash holding, which reflects managers' information and endogenous precautionary reaction. This strategy follows Acharya et al. (2012) who propose that when constraints on external financing are binding, managers accumulate cash reserves as a precautionary measure in order to reduce the risk of financial default. However, this does not entirely offset the default risk. At the end, firms with higher default risk whose external financing is constrained exhibit both higher levels of cash and higher default spreads on their debt.

Evidence shows that firms commonly accumulate cash if they foresee problems in raising capital. Farre-Mensa and Ljungqvist (2016) find that corporate cash holdings are twice as high for firms that are classified as constrained than for unconstrained firms. Thus the level of cash held by firms reflects managerial private information about the firm's cash needs and about whether they view their financing as being strained. This information is superior to the information provided by common measures of financial constraint, which Farre-Mensa and Ljungqvist (2016) consider inadequate to gauge the extent of financial constraint. Given managerial superior information, it is possible to infer from the firm's cash holdings about the managers' private information about foreseen constraints on external financing. (e.g., Buehlmaier and Whited, 2018), who find that highly constrained firms, according to their textual measures, hold remarkably higher cash balances. It follows that the level of corporate cash informs about the managers' views on their firms' financing restrictions.[26]

We use the observed level of cash as an indicator of the managerial information about future cash needs and the firm's potential financing restrictions. Riddick and Whited (2009, p. 1730) propose that precautionary holding of cash is motivated by income uncertainty and by the cost of external financing. To focus on the latter we control for the uncertainty motive for cash hoarding by following Opler et al. (1999) who find a positive effect on cash holdings of the firm cash flow volatility[27] measured by Sigma, the standard deviation of annual cash flow scaled by net assets, where cash flow is net income minus dividend plus depreciation and net assets are total assets minus cash. We estimate Sigma as the standard deviation of quarterly cash flow divided by net assets over the recent 12 quarters. We require at least 6 quarters with non-missing cash flow data. Opler et al. (1999) find that the firm's Sigma and the average industry Sigma have a strong positive effect on cash holdings. We control for the firm's Sigma and include industry Sigma, defined as the average of firm cash flow volatility across industries (using the 2-digit SIC code) that control for industry volatility and for other industry-related determinants of cash holdings.

The estimation procedure is as follows. In each quarter we estimate a cross section regression of cash holding on Sigma and on industry Sigma variables, where cash holding is cash plus marketable securities scaled by net assets. The residuals from this regression, the cash level after controlling for the uncertainty motive for holding cash and for industry characteristics, are construed as indicating the managerial precautionary cash holdings due to foreseen credit risk and foreseen difficulty in raising capital. We then divide the sample in the following quarter into two halves by whether the firm's residual cash holding is above or below the median. Finally, we conduct a panel regression estimation of our base model of

[26]In terms of our model, high cash can be seen as a proxy for low pledgeability (the parameter τ).

[27]Kim et al. (1998) find both theoretically and empirically that volatility induces higher cash holdings.

Table 4, Panel A, separately for the high-residual cash and low-residual cash subsamples. We then conduct two robustness checks. First, we repeat the above procedure after eliminating in each quarter the top 10% largest firms in terms of total asset value in the previous quarter, or after eliminating firms with positive pre-tax foreign income which induces them to hold excess cash.

We expect that for firms with high residual cash holding there is a stronger positive relation between operational spread, proxied by *Markup* which is the dependent variable, and the credit spread, proxied by -(z-score) or a stronger positive relation between markup leverage, especially the part of the debt which matures in the next two years. For firms with low residual cash we expect these relationships to be muted or non-existent.

The results are presented in Table 4, Panel B. Consistent with our expectation, the effects of -(z-score) and leverage are positive and significant for the half sample of firms with high lagged level of residual cash while being insignificant for half of the sample with low lagged level of residual cash. This supports our model's prediction on a stronger tradeoff between financial hedging and operational hedging for firms with difficulties in raising funds. When we separate between leverage that short-term and long-term, the coefficient of term leverage maturing in the next two years is positive and statistically significant, while the coefficient of the remaining long-term leverage is insignificant or marginally significant for both high and low residual cash holding subsamples (columns (3) and (7)). The coefficient of leverage maturing in the next two years for the high-residual cash subsample is about four times larger than it is for the low-residual cash firms. In the final regression for low-residual cash firms in column (8) we find that the effects of all variables are insignificant, both economically and statistically, which strongly contrasts with the significant effects of -(z-score) and of short-term debt for high-residual cash firms in column (4).

We address the concern that large or multinational firms have abnormally high cash holdings which are unrelated to the managerial precautionary motive for cash accumulation. Thus, in Panel C of Table 4 we repeat the above exercise excluding the top 10% largest firms in each quarter in terms of lagged total assets, and in Panel D of Table 4 we exclude firms with positive pre-tax foreign income as of the most recent fiscal year end. These exclusions do not have a qualitative effect on the results. The patterns of the estimated coefficients in Panels C and D of Table 4 are not meaningfully different from those in Panel B.[28]

We conclude that our estimation results are consistent with our model's predictions and the numerical results in Section 4 that for operational hedging is more strongly affected by credit risk and by cash needs for low-pledgeability firms, indicated by low τ, which indicates a financing difficulty. Empirically, the operational spread is positively affected by credit spread and leverage only for firms where accumulated cash indicates managerial information of a financial risk together with difficulty in raising funds to mitigate it, which we do not find such a relation for firms with low accumulated cash.

5.5 Recessions periods

During recession periods, firms' liquidity needs can be higher, either due to lower pledgeability of their future cash flows (lower τ), or due to higher level of net indebtedness ($\bar{F}$).[29] Consequently, the tension between financial hedging and operational hedging is intensified during the recessions.

In this section, we augment the baseline estimation in Table 4 with interaction terms between firms' liquidity position indicators and a dummy variable for recession periods according to NBER and the dummy variable itself. We notice that many firm-level variables fluctuate over the business cycles, which can be empirically questionable (Roberts and Whited, 2013). Correspondingly, we fix our right hand-side variables, other than the dummy variable for recession, during recession periods, at their respective values as of the most recent quarter before the starts of the recession periods.

Table 5 presents the results. Panel A shows that firms entering recession periods with higher -(Z-score) and Leverage witness more prominent increases in markup, indicated by the positive and statistically significant coefficients on the interaction terms between -(Z-score)

[28] Our results are robust as well if we exclude firms in the high-tech industry.

[29] For the impact of business cycles on firms' pledgeability, please refer to, for example, Fernández-Villaverde and Guerrón-Quintana (2020).

and recession, as well as between Leverage and Recession. Panel B shows that firms with more precarious liquidity positions at the onset of recessions, measured by either -(Z-score) or Leverage, decreases in inventory-sales ratio, indicated by the negative and statistically significant coefficients on the interaction terms between -(Z-score) and Recession, as well as between Leverage and Recession. The collective evidence from columns (1) to (4) is consistent with our model predictions: firms with higher liquidity needs to meet debt obligations cut their operational hedging more, in terms of inventory holding, during the recessions, when they face a higher frictional external financing environments. This, in turn, is concomitant with a more prominent increase in markup during the recessions for the same group of firms.[30] Panel C and D examine the two measures of supply chain diversification. We do not find any statistically significant relationship between firms' supply chain adjustment during the recessions and their pre-recession liquidity positions.[31]

Table 6 presents the impact of firms' pre-recession -(Z-score) and Leverage on their markups and inventory as recession progresses. Specifically, we break down the recession indicator into quarter indicators relative to the onset of each recession, from 4 quarters before to 4 quarters into recessions, as well as beyond 4 quarters into the recessions. We also perform a F-test for joint significance of the interaction terms between pre-recession liquidity positions and quarter indicators for the four quarters' periods before and after the onset of recessions. In Panel A, we find that the firms' pre-recession -(Z-score) and Leverage affect their markup mostly within the first four-quarter periods into recessions. Interestingly, the coefficients of the interaction terms between Leverage and the pre-recession four quarters are jointly statistically significant below 10%. In Panel B, we find that firms with higher

[30] However, one should interpret the results with caution. It is well known that recessions can cause demand slumps and economic distresses in the corporate sector, both of which can lead a drop in inventory holding. Such inventory adjustments can be more pronounced for firms with more precarious pre-recession liquidity positions, if these firms happen to be more pro-cyclical. The next subsection provides a cleaner test using the subprime mortgage crisis. Originated from housing sector, rather than the corporate sector, using the subprime mortgage crisis as a natural experiment setting is less susceptible to the above criticism.

[31] Related to the insignificant results, we find that the most prominent determinant of the supply chain diversification (SCD hereafter) is firm fixed effects. Consequently, SCD measures do not exhibit much time-series variation. In untabulated results, we regress the two measures of SCD against the control variables in our baseline model. The R-squared increases significantly once we have firm fixed effects in the regressions, whereas quarter fixed effects do not increase the R-squared noticeably.

-(Z-score) or Leverage before the recession reduce their inventory holdings starting from the second quarter into recession, and continue to do so beyond the fourth quarter into recessions. Interestingly, those firms also have higher inventory holdings during three and four quarter periods before the recession.

5.6 Effect of financial constraint: the consequences of a shock to credit supply

We exploit the financial shocks during the crisis of 2008 to capture time series variation in firms' ability to raise external finance: When firms' ability to raise external finance is lower, there is a stronger effect of its credit risk and leverage on operational hedging. During the financial crisis of 2008, a number of banks could no longer extend credit to firms with which they had lending relationship beforehand. We test whether for firms that were adversely affected by this shock to credit, the effect of -(Z-score) or Leverage on markup became stronger. A shock to a lender increases the firm's propensity to use more resources to avoid financial default, which comes at the expense of spending on operational hedging. Consequently, a firm whose lender is negatively shocked, more aggressively reduces its cost and consequently its Markup increases by more for any given level of -(z-score) or leverage.

We first find the relationship between our sample firms and bank lenders using data from the LPC-Dealscan database. We then follow Chodorow-Reich (2014) who use three variables to measure the negative impact of the subprime mortgage crisis on lenders' abilities to extend credit to the borrowers.[32] The first variable (% # Loans) is a direct measure of changes in loan supply for a firm's lenders. For each lender, it calculates the Proportional changes in the (weighted) number of loans that the lender extended to all the firms other than the firm in question, between the 9-month period from October 2008 to June 2009, and the average of 18-month period containing October 2005 to June 2006 and October 2006 to June 2007. The weight is the lender's share of each loan package commitment. The second measure (Lehman exposure) is Lehman exposure, the exposure to Lehman Brothers through

[32]We thank Chodorow-Reich for sharing his data with us.

the fraction of a bank's syndication portfolio where Lehman Brothers had a lead role. The third measure (ABX exposure) captures banks' exposure to toxic mortgage-backed securities, which is calculated using the correlation between banks' daily stock return and the return on the ABX AAA 2006-H1 index. Then, for each firm and each of the three variables, it calculates a weighted average of the measure over all members of the last pre-crisis loan syndicate of the firm, in which the weight is each lender's share in the firm's last pre-crisis loan syndicate. The detailed constructions of the three variables are in Chodorow-Reich (2014). We construct the three variables in a way so that a larger value implies a larger exposure to the financial crisis on the lenders' side. For this analysis, we restrict our sample firms to the $2,429$ firms in Chodorow-Reich (2014).

We use the following regression specification.

$$\begin{aligned} Markup_{j,t} = \alpha + \beta_1 \times X_{j,2007} \times Lender\ exposure_{j,t} + \beta_2 \times Lender\ exposure_{j,t} \\ + \sum_m \beta_{3,m} \times Control\ variable_{m,j,t-1} \\ + \sum_k \beta_{4,m} \times Controls\ variables_{m,j,t-1} \times Lender\ exposure_{j,t} + \theta_j + \eta_t + \epsilon_{j,t} \end{aligned} \tag{5.2}$$

We estimate the differential effect on $Markup_{j,t}$ for firms that entered the post-crisis period with different levels $X_{j,2007}$ being either -(Z-score) or Leverage, given different levels of the firm's exposure to the crisis. Notably, $X_{j,2007}$ is fixed before the crisis as of the end of 2007. The comparison is between the two-year period before the crisis (July 2006 to June 2008) and the two-year period after the crisis (January 2009 to December 2010). The lenders' exposure to the financial crisis equals zero for the two-year period before the crisis, and equals its actual respective values for the two-year period after the crisis. The control variables are the same as in the baseline regression (Table 4) and they are fixed at the end of year 2007 for the post-crisis years, to be consistent with $X_{j,2007}$. Our test focuses on β_1, the coefficient of the interaction between the crisis exposure and the credit risk variables. The model includes firm and year-quarter fixed effects and standard errors are at firm levels.[33]

[33] Our results are qualitatively similar if we cluster the standard errors at both firm and year-quarter levels.

Naturally, in these regressions which are confined to a short time period, the number of observations is much smaller.

[INSERT Table 7.]

Table 7 presents the results. We find that the coefficient β_1 is positive and significant for all interactive terms except for the $-$(z-score) $\times$ Lehman exposure. Our results mean that the effect of credit risk, proxied by -(z-score), or leverage, was greater for firms whose lenders were adversely affected by the financial crisis. These firms were forced to reduce spending on operational hedging, which we capture by the widening of markup, because of their needs to avoid financial default. To gauge the economic significance of the joint impacts of the firm's credit risk and its exposure to financial crisis on the borrower's operational spread, taking column (1) as an example, one unit increase in the firm's negative z-score yields additional 0.009 markup when the firm's lenders reduce number of loans to other borrowers by 10% more during the financial crisis. Column (2) shows that a firms that enters the crisis period with 0.1 higher leverage ratio will increase its markup by an additional 0.007 when the firm's lenders reduce number of loans to other borrowers by 10% more during the financial crisis. According to column (3), a firm that enters the crisis period with 0.01 higher short-term leverage ratio witnesses an additional 0.003 markup when the firm's lenders reduce number of loans to other borrowers by 10% more during the financial crisis, while a firm that enters the crisis period with 0.01 higher long-term leverage ratio witnesses 0.0005 change in markup when its lenders has the same exposure to the crisis. This is consistent with our results in Table 4, column (3), which represents a near-term liquidity need, proxied by the amount of leverage maturing in the near future, has a stronger effect on Markup than the long-term leverage. Using two alternative exposures to financial crisis yields qualitatively similar results.

Next, we turn to the correlations between post-crisis inventory and supply chain adjustments and firms' related bank exposure to the crisis. Panel B — D present the results. For inventory, we find that firms with higher overall leverage before the crisis witness larger drops in inventory, proportional to sales, in post-crisis periods, if their lenders are more exposed to the crisis, as shown by the negative and significant coefficients on the interaction terms between Leverage and Lender exposure in Panel B. Firms' pre-crisis -(Z-score) cease to matter in post-crisis inventory adjustments, indicated by insignificant, albeit negative coefficients on the interaction terms between -(Z-score) and Lender exposure. Panel C and D present the results regarding the post-crisis supply chain adjustments. We find that firms entering the crisis with more precarious liquidity positions, measured by either higher -(Z-score) or higher Leverage, refocus their supply chains in post-crisis period, if their lenders are more closely connected to Lehman Brothers, or more exposed to asset-backed security market, as indicated by the negative and significant coefficients on the interaction terms between either -(Z-score) or Leverage and Lender exposure, in columns (3) — (6) of Panel C and D. However, the above results are not robust if we measure lenders' exposure to financial crisis using proportional changes in loan supply by firms' lenders during the crisis. Overall, the results on inventory and supply chain diversification are less robust. We conjecture that to meet the acute liquidity demand driven by the financial crisis, firms increase their short-term profits (markup) by simultaneously raising their product prices and cutting the costs of production, such as operational hedging costs. The determinants of tapping the price channel versus cost channel are a fruitful area for future research.

One concern about the above results is that the interaction between the exposure of the firm' s lender to the financial crisis and the firm' s financial vulnerability — leverage and -Z score — indicates firm characteristics which in turn affect the firm' s markup. We address this concern by studying the dynamic effects of this interaction term before and after the crisis. If markup is affected by the interaction term before the crisis, then this relationship is not a result of change in financing conditions imposed on the firm as a result of the crisis. Specifically, we replace *Lender Exposure* variable in equation (5.2) with the interaction terms (*Lender exposure*, D_n) between the actual magnitudes of lender exposure to the financial crisis and quarter indicators for the four quarters before and four quarters, as well as from five to eight quarters after the financial crisis.

Table 8 presents the results. In all columns, the joint effects of lender's exposure and the firms' credit risk are mostly significant after the crisis while being insignificant before the crisis. This indicates that for financially vulnerable firms — those with higher -(Z-score) and Leverage — deterioration in financing conditions imposed on firms whose lenders were more strongly exposed to the financial crisis forced them to reduce their operational hedging, which is reflected by the widening of their Markup. This relationship occurred only after the crisis but not before it. At the bottom of each column we present F-tests of the joint significance of all the coefficients of the interaction terms, conducted separately for the four quarters before the crisis and the four quarters after it. In all tests, the F-value shows strong statistical significance of the coefficients of the interaction terms for the post-crisis four quarters while it shows insignificance of the coefficients of the pre-crisis four quarters.

[INSERT Table 8.]

Overall, the results show that the tension between operational hedging spending and the needs to avoid financial default is stronger when the firm is hit by a negative shock to its ability to raise capital. Then, it foregoes spending on operational hedging activities and diverts cash to service its financial needs.

6. Conclusion

In this paper, we studied the corporate choice between financial efficiency and operational resiliency. We built a model in which a competitive (pricing-taking) firm substitutes between saving cash for financial hedging, which mitigates the risk of financial default, and spending on operational hedging, which mitigates the risk of operational default such as a failure to deliver on obligations to customers. This tradeoff is particularly strong for firms that face difficulty raising external finance and results in a positive relationship between operational spread (markup) and financial leverage or credit risk.

We presented empirical evidence supporting our model predictions. First, we documented that markup is a reasonable summary of firms' operational hedging activities, measured as inventory holdings and supply chain diversification, as our model implies. Then we documented a positive relationship between a firm's credit risk, measured as -(Z-score), total financial leverage, as well as the near-term portion of long-term leverage. This positive relationship is stronger when firms have a greater motivation to hoard liquidity in order to avert financial default, and it increases in the aftermath of the subprime financial crisis for firms whose lenders were more exposed to the financial crisis. Moreover, we showed that firms that entered the subprime financial crisis with high credit risks increased their markup by a larger extent if their lenders were more exposed to the financial crisis. Overall, our empirical findings confirm our model prediction that the tension between financial and operational hedging is more pronounced when firms face greater difficulty raising external funds.

While our paper takes a first step towards understanding the tension between financial efficiency and operational resiliency, which manifested during the recent Covid-19 pandemic, more theoretical and empirical analyses along this line of research are needed. On the theoretical end, one can build a general equilibrium model that extends the current partial equilibrium framework to a production network model in which product pricing, financial (leverage) and operational hedging decisions are determined as equilibrium outcomes of the entire system, with firm's operational hedging determining the operational hazard for its upstream and downstream firms in the network. Such a model can be used to analyze production network externalities in operational hedging such as underinvestment in operational resiliency arising from leverage spillovers across firms. On the empirical end, a more detailed research on forms of operational hedging, understanding their relative tradeoffs, and identifying their linkage to product prices with a microscope, are needed; all of this requires gathering of richer data on operational hedging. We leave these exciting extensions for future research.

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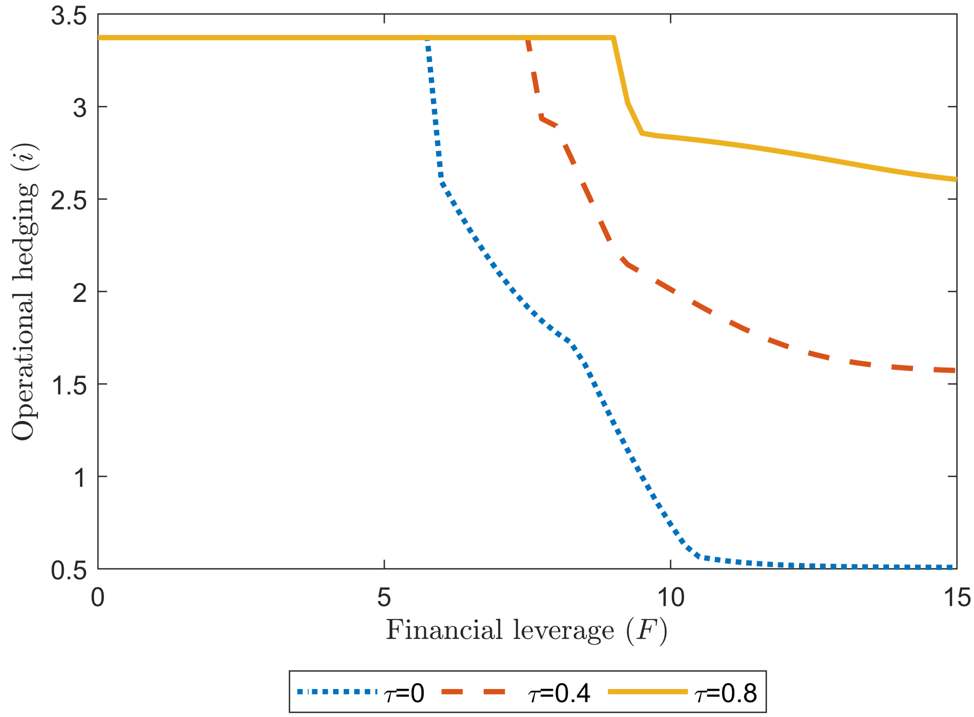

Figure 1: **Firm's optimal hedging policy i^{**} and debt level F**

Optimal hedging policy i^{**} given debt level F for $\tau = 0$, $\tau = 0.4$ and $\tau = 0.8$. All other parameters are presented in Table 1.

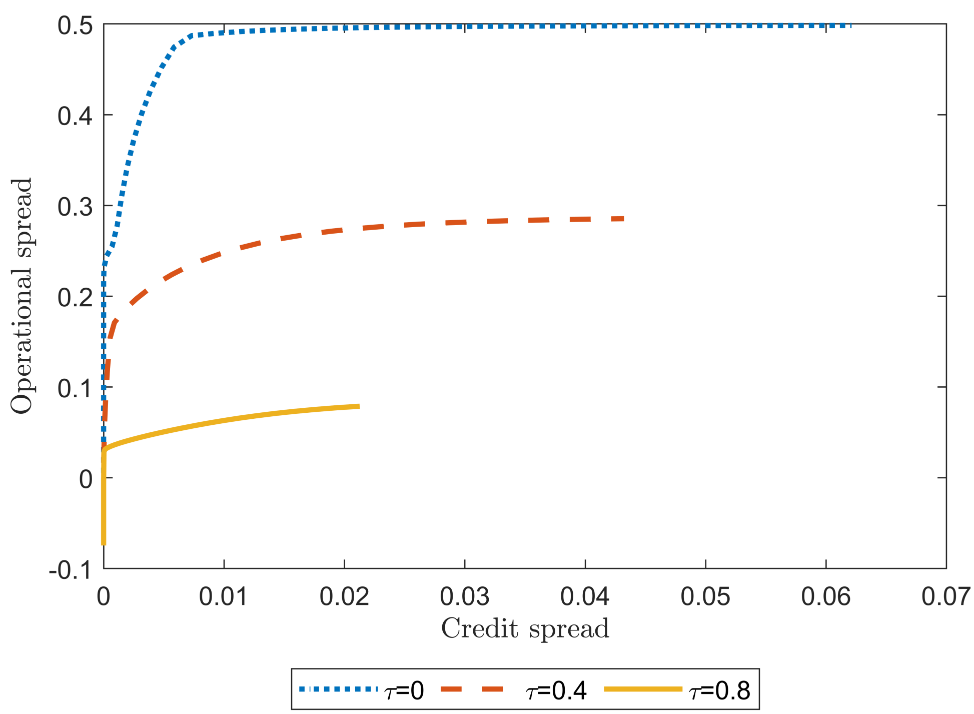

Figure 2: **Credit spread and operational spread**

The credit spread and operational spread under the optimal hedging policy i^{**} given debt level F for $\tau = 0$, $\tau = 0.4$ and $\tau = 0.8$. All other parameters are presented in Table 1.

Figure 5A: -(Z-score) and markup

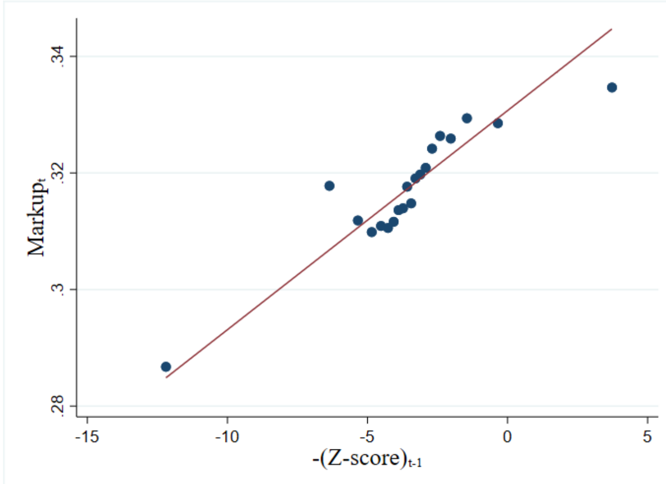

Figure 5B: Financial leverage and markup

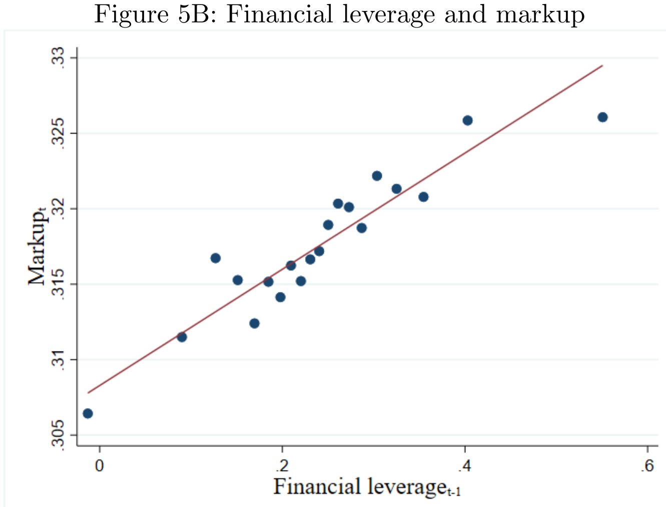

Figure 3: **Markup and Credit risk**

We first residualize the y-axis variable and x-axis variable with respect to the baseline control vector (including the fixed effects) in Table 4. We then add back the unconditional mean of the y and x variables in the estimation sample to facilitate interpretation of the scale. Finally we divide the (residualized) x-axis variable into twenty equal-sized groups (vingtiles) and plot the means of the y-variable within each bin against the mean value of x-variable within each bin.

Table 1: **Parameter values for numerical analysis**

The table presents the parameter values used for the numerical analyses in Section 4.

Parameter	Interpretation	Value
α	Rate of the exponential distribution of u	0.05
I	Contractual delivery amount	3
κ	Production cost parameter	0.1
λ	Proportional cost of operational default	0.5
p	Unit price	1.2
t	Tax rate	0.3
x_0	Cash flow at date-0	5
$\bar{x}_1$	Certain cash flow at date-1	5
x_2	Franchise value at date-2	10

Table 2: **Summary statistics** — COMPUSTAT 1973-2020

Summary statistics of the variables in our sample from 1971 to April 2020. The data are quarterly from COMPUSTAT; The variable names are in parentheses. Markup = (sales(SALEQ) − cost of goods sold(COGSQ))/$Sales$. Z-score is Altman (2013)'s measure calculated from quarterly data. Leverage = (long-term debt(DLTTQ) + short-term debt(DLCQ))/total assets(ATQ). Long-term debt maturing in the next 2 years = $(DD1 + DD2)$ according to the most recent fiscal year-end divided by total assets. Remaining long-term leverage = $(DLTTQ - DD2)$ divided by total assets. Tobin's Q = (common shares outstanding(CHOQ)×stock price at the close of the fiscal quarter(PRCCQ)+ preferred stock value(PSTKQ) + dividends on preferred stock(DVPQ) + liabilities(LTQ))/total assets. Cash holdings ($CHEQ$), Cash flow (= $IBQ + DPQ$) and Tangible assets ($PPENTQ$) are divided by Total assets. Market power is measured by three variables, all employing Fama and French's 38 industries: a dummy variable for the top 3 industry seller = 1 if the firm's sales are among the top three sellers in the industry (0 otherwise); Firm's Sales/Industry sales; and Herfindahl index. The operational hedging variables include Inventory ($INVQ$)/Sales, Supply chain diversification index, and Supply chain diversification ranking. The supply chain variables are composed from three raw measures: (i) log(1+number of suppliers), (ii) log(1+number of supplier regions), (iii) log(1+number of suppliers not from the firm's region). Data are quarterly (source: Factset), covering 6,204 firms from mid-2003 to the first quarter of 2020. Supply chain diversification index is the first principal component score from a principal component analysis (PCA) that equals 0.5745 × (i) + 0.5796 × (ii) + 0.5779 × (iii) where (i)-(iii) indicate the above three measures. Supply chain diversification ranking is negative value of the average ranking of the firm-quarter ranking in terms of each of the individual measures. A larger value of the supply chain diversification ranking indicates a more diversified supply chain network.

The sample requires that the lagged firm capitalization is at least \$10 million and quarterly sales are at least \$1 million (inflation adjusted to the end of 2019). All continuous variables are winsorized at both the 1st and 99th percentiles.

VARIABLES	N	Mean	S.D.	P25	P50	P75
Markup: (sales-cogs)/sales (sales-cogs)/sales	599,677	0.318	0.426	0.207	0.337	0.508
-(Z-score)	572,345	-3.538	5.857	-3.993	-2.082	-1.082
Financial leverage	584,150	0.241	0.215	0.049	0.209	0.367
Long-term debt maturing in the next 2 years/total assets	503,420	0.049	0.078	0.00026	0.018	0.061
Remaining long-term leverage	504,118	0.158	0.181	0.000	0.102	0.256
Tobin's Q	599,677	1.961	1.576	1.069	1.435	2.184
Cash holdings	599,677	0.161	0.195	0.023	0.079	0.225
Cash flow	599,677	0.010	0.055	0.006	0.021	0.035
Asset tangibility	599,677	0.308	0.246	0.105	0.239	0.458
Total assets	599,677	2,886.763	8,681.261	82.851	318.012	1,433.546
Dummy variable for the top 3 industry seller	599,677	0.024	0.152	0.000	0.000	0.000
Sales/industry sales	599,677	0.007	0.020	0.000	0.001	0.003
Herfindahl index	599,677	0.067	0.063	0.033	0.047	0.077
Inventory/sales	588,365	0.491	0.534	0.062	0.379	0.713
Supply chain diversification index	116,320	-0.009	1.697	-1.334	-0.381	0.964
Supply chain diversification ranking	116,320	-0.500	0.268	-0.730	-0.515	-0.274

Table 3: **Markup and operational hedging**

Estimation of the relationship between Markup and measures of operational hedging. The variables are defined in Table 2. The control variables include Tobin's Q, ln(Total assets), Cash holdings, Cash flow, Tangible assets, a dummy variable for the top 3 industry seller, Sales/total sales, and Herfindahl index. All explanatory variables are lagged by one quarter. The regressions include firm and year-quarter fixed effects. Standard errors are clustered at firm and year-quarter levels. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively.

VARIABLES	*Markup*	
	(1)	(2)
Supply chain diversification index	-0.0070***	
	(0.0026)	
Supply chain diversification ranking		-0.041***
		(0.015)
Inventory/sales	-0.043***	-0.043***
	(0.015)	(0.015)
Control variables	Yes	
Firm fixed effects	Yes	
Year-quarter fixed effects	Yes	
Observations	116,068	116,068
R-squared	0.739	0.739

Table 4: **Markup and credit risk**

Estimation of the relationship between Markup, -(Z-score) and Leverage. The dependent variable in the panel regression is the quarterly Markup. Leverage is divided into the short-term debt maturing in two years and the remainder, both scaled by total assets. Panel A presents the full-sample estimation. Panel B presents separate estimations, for firms with high and low financial constraint in the previous quarter. Financial constraint is measured by cash holdings after controlling for risk and industry characteristics. In each quarter, cash holding (cash plus marketable assets divided by net assets, which is total assets minus cash) is regressed across firms on cash flow volatility (the standard deviation over 12 quarters of cash flow divided by net assets) and industry cash flow volatility, defined as the average firm cash flow volatility for each industry (using 2-digit SIC code). Then, the sample of firms is divided into two halves by whether the firm's residual cash holding is above or below the median. Firms with above-median residual cash holdings are classified as constrained firms. Panel C and Panel D repeat the analyses in Panel B, excluding the top 10% largest firms in terms of total asset value in the previous quarter, and firms with positive pre-tax foreign incomes as of the most recent fiscal year-end, respectively. The control variables include Tobin's Q, ln(Total assets), Cash holdings, Cash flow, Tangible assets, a dummy variable for the top 3 industry seller, Sales/total sales, and Herfindahl index. All explanatory variables are lagged by one quarter. The regressions include year-quarter and firm fixed effects. Standard errors are clustered at firm and year-quarter levels. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively. The complete table is presented in Table IA.1.

Panel A: Full sample

VARIABLES	*Markup*			
	(1)	(2)	(3)	(4)
-(Z-score)	0.0038***			0.0039***
	(0.00057)			(0.00062)
Financial leverage		0.039***		
		(0.011)		
Long-term debt maturing in the next 2 years/total assets			0.073***	0.041**
			(0.018)	(0.017)
Remaining long-term leverage			0.037***	0.0081
			(0.012)	(0.012)
Control variables	Yes			
Firm fixed effects	Yes			
Year-quarter fixed effects	Yes			
Observations	571,388	583,162	504,688	477,938
R-squared	0.614	0.608	0.625	0.631

Panel B: High v.s. low residual cash

VARIABLES	*Markup*							
	High residual cash				Low residual cash			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-(Z-score)	0.0040***			0.0039***	0.00091			0.0018*
	(0.00091)			(0.00094)	(0.00084)			(0.00096)
Financial leverage		0.075***				-0.0023		
		(0.024)				(0.012)		
Long-term debt maturing in the next 2 years/total assets			0.175***	0.142***			0.039**	0.021
			(0.049)	(0.047)			(0.017)	(0.017)
Remaining long-term leverage			0.055**	0.013			0.014	0.0049
			(0.025)	(0.024)			(0.013)	(0.013)
Control variables	Yes							
Firm fixed effects	Yes							
Year-quarter fixed effects	Yes							
Observations	219,742	222,039	198,427	189,579	216,156	223,480	189,120	178,139
R-squared	0.719	0.716	0.727	0.730	0.498	0.496	0.516	0.515

Panel C: High v.s. low residual cash (Excluding large firms)

VARIABLES	*Markup*							
	High residual cash				Low residual cash			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-(Z-score)	0.0040***			0.0040***	0.00055			0.0014
	(0.00095)			(0.00098)	(0.00080)			(0.00090)
Financial leverage		0.075**				-0.012		
		(0.029)				(0.013)		
Long-term debt maturing in the next 2 years/total assets			0.172***	0.137**			0.029	0.015
			(0.056)	(0.053)			(0.018)	(0.019)
Remaining long-term leverage			0.051	0.0055			0.0081	0.00014
			(0.031)	(0.030)			(0.014)	(0.015)
Control variables	Yes							
Firm fixed effects	Yes							
Year-quarter fixed effects	Yes							
Observations	179,603	179,482	161,092	155,434	176,114	180,406	151,290	143,897
R-squared	0.719	0.717	0.728	0.731	0.500	0.498	0.521	0.521

Panel D: High v.s. low residual cash (Excluding firms with positive foreign income)

VARIABLES	*Markup*							
	High residual cash				Low residual cash			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-(Z-score)	0.0048***			0.0047***	0.0012			0.0022**
	(0.0011)			(0.0011)	(0.00092)			(0.0011)
Financial leverage		0.097***				-0.0023		
		(0.030)				(0.015)		
Long-term debt maturing in the next 2 years/total assets			0.183***	0.146**			0.036*	0.016
			(0.057)	(0.056)			(0.021)	(0.022)
Remaining long-term leverage			0.079**	0.030			0.014	0.0029
			(0.031)	(0.030)			(0.016)	(0.017)
Control variables	Yes							
Firm fixed effects	Yes							
Year-quarter fixed effects	Yes							
Observations	156,751	159,690	141,358	134,265	154,779	160,422	133,637	125,317
R-squared	0.714	0.711	0.722	0.725	0.486	0.483	0.504	0.504

Table 5: **Operational hedging and credit risk: NBER recessions**

Regressions of Markup, Inventory and Supply chain diversification on firms' -(Z-score) and Leverage that interact with NBER recession years. *Recession* = 1 if the quarter is classified as NBER recession, and = 0 otherwise. For each recession, the values of -(Z-score), Leverage and control variables during recession periods are fixed as of the most recent quarter before the onset of the recession. The firm-level control variables are as in Table 4. Panel A examines markup. Panel B examines inventory- sales ratio. Panels C and D examine the two measures of supply chain diversification (SCD) variables — Supply chain diversification index (SCD index) and Supply chain diversification ranking (SCD ranking), respectively. The variable definitions are in Table 2. The regressions include firm and year-quarter fixed effects. Standard errors are clustered by firm and year-quarter levels. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively.

VARIABLES	Panel A: *Markup*		Panel B: *Inventory/sales*		Panel C: *SCD index*		Panel D: *SCD ranking*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-(Z-score) × Recession	0.002**		-0.002***		-0.003		-0.000	
	(0.001)		(0.001)		(0.002)		(0.000)	
-(Z-score)	0.004***		-0.003***		0.010***		0.002***	
	(0.001)		(0.000)		(0.002)		(0.000)	
Leverage × Recession		0.041***		-0.034**		-0.019		0.002
		(0.013)		(0.013)		(0.069)		(0.013)
Leverage		0.037***		-0.032***		0.117*		0.024**
		(0.011)		(0.010)		(0.064)		(0.011)
Control variables				Yes				
Firm fixed effects				Yes				
Year-quarter fixed effects				Yes				
Observations	564,533	576,114	553,303	563,893	113,404	116,268	113,404	116,268
R-squared	0.616	0.609	0.716	0.725	0.850	0.852	0.803	0.804

Table 6: **Markup, inventory and credit risk: Dynamic effects of NBER recessions**

Regressions of Markup and Inventory- sales ratio on the firms' financial variables indicated by Y, representing either the pre-recession -(Z-score) or the pre-recession leverage, that interact with quarter indicator variable, D_n, $n = -1, -2, -3, -4, +1, +2, +3, +4, +4+$ relative to the onset of each recession, from 4 quarters before to 4 quarters into recessions, as well as beyond 4 quarters into the recessions (n = 4+). The default category (omitted in the regressions) is the indicator for more than 4 quarters before the recessions. For each recession, the values of -(Z-score) and Leverage during recession periods and the four-quarter periods before the onset of recession are fixed as of the most recent quarter before the onset of the recession. Similarly, the values of the control variables during recession periods are fixed as of the most recent quarter before the onset of the recession. The firm-level control variables are those included in Table 4. The last two rows present the results from an F-test for joint significance of the coefficients of the interaction terms between Y and quarters D_n, where $n = +1, +2, +3, +4, +4+$ and for quarters $n = -1, -2, -3, -4$ relative to the start of the recessions. The regressions include firm and year-quarter fixed effects. Standard errors are clustered by firm and year-quarter levels. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively.

VARIABLES	Panel A: *Markup*		Panel B: *Inventory/sales*	
	$Y = -(Z - score)$	$Y = Leverage$	$Y = -(Z - score)$	$Y = Leverage$
	(1)	(2)	(3)	(4)
$Y \times D_{+4+}$	0.001	0.015	-0.002***	-0.062***
	(0.001)	(0.019)	(0.001)	(0.016)
$Y \times D_{+4}$	0.001	0.044**	-0.002**	-0.037**
	(0.001)	(0.018)	(0.001)	(0.017)
$Y \times D_{+3}$	0.002***	0.050***	-0.003***	-0.050***
	(0.001)	(0.015)	(0.001)	(0.014)
$Y \times D_{+2}$	0.003***	0.064***	-0.002***	-0.024*
	(0.001)	(0.014)	(0.001)	(0.014)
$Y \times D_{+1}$	0.001*	0.065***	-0.001	-0.006
	(0.001)	(0.013)	(0.001)	(0.013)
$Y \times D_{-1}$	-0.001	0.024*	0.000	0.010
	(0.001)	(0.013)	(0.001)	(0.012)
$Y \times D_{-2}$	-0.000	0.019	0.000	0.012
	(0.001)	(0.012)	(0.001)	(0.012)
$Y \times D_{-3}$	-0.000	0.022*	0.001*	0.029**
	(0.001)	(0.012)	(0.001)	(0.012)
$Y \times D_{-4}$	-0.000	-0.004	0.002***	0.019
	(0.001)	(0.012)	(0.001)	(0.013)
Y	0.003***	0.027***	-0.003***	-0.026***
	(0.001)	(0.010)	(0.000)	(0.010)
Control variables		Yes		
Firm fixed effects		Yes		
Year-quarter fixed effects		Yes		
Observations	561,812	575,483	551,025	563,840
R-squared	0.615	0.609	0.717	0.726
F-statistic for $n = +1$ to $+4$	4.00***	7.57***	4.11***	3.86***
F-statistic for $n = -1$ to -4	0.22	2.01*	3.23**	1.57

Table 7: **Operational hedging and credit risk: Exposure to the financial crisis**

Regressions of Markup, Inventory- sales ratio and supply chain diversification on firms' -(Z-score) and Leverage that interact with the extent of exposures to the 2008 financial crisis. The sample firms includes the $2,429$ firms in Chodorow-Reich (2014). The two-year periods before and after the crisis are July 2006 to June 2008, and January 2009 to December 2010, respectively. The three measures for crisis exposure are % # Loans reduction, Lehman exposure and ABX exposure, using Chodorow-Reich (2014)'s variables. The lenders' exposure to the financial crisis equals zero for the two-year period before the crisis, and equals its actual respective values for the two-year period after the crisis. The values of -(Z-score) and Leverage are as of the end of 2007. The firm-level control variables, as in Table 4, are fixed at the end of 2007 for the entire post-crisis periods. The specification is as in the model $Markup_{j,t} = \alpha + \beta_1 \times X_{j,2007} \times Lender\ exposure_{j,t} + \beta_2 \times Lender\ exposure_{j,t} + \sum_m \beta_{3,m} \times Control\ variable_{m,j,t-1} + \sum_k \beta_{4,m} \times Controls\ variables_{m,j,t-1} \times Lender\ exposure_{j,t} + \theta_j + \eta_t + \epsilon_{j,t}$. Panel A examines Markup. Panel B examines Inventory- sales ratio. Panel C and D examine the two measures of supply chain diversification (SCD) — Supply chain diversification index (SCD index) and Supply chain diversification ranking (SCD ranking), respectively. The variable definitions are in Table 2. The regressions include year-quarter and firm fixed effects. Standard errors are clustered by firm. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively.

Panel A: Markup and credit risk: Exposure to the financial crisis

	% # Loans reduction		Lehman exposure		ABX exposure	
VARIABLES	*Markup*					
	(1)	(2)	(3)	(4)	(5)	(6)
-(Z-score) × lender exposure	0.085***		0.157**		0.080***	
	(0.032)		(0.068)		(0.026)	
Leverage × lender exposure		0.712**		1.078*		0.571**
		(0.290)		(0.562)		(0.257)
Lender exposure	-0.067	-0.289	-0.072	-0.302	-0.329	-0.438
	(0.453)	(0.465)	(0.794)	(0.837)	(0.424)	(0.423)
Control variables	Yes					
Control variables × lender exposure	Yes					
Firm fixed effects	Yes					
Year-quarter fixed effects	Yes					
Observations	20,926	21,827	20,926	21,827	20,926	21,827
R-squared	0.897	0.893	0.897	0.893	0.897	0.893

Panel B: Inventory and credit risk: Exposure to the financial crisis

	% # Loans reduction		Lehman exposure		ABX exposure	
VARIABLES	*Inventory/sales*					
	(1)	(2)	(3)	(4)	(5)	(6)
-(Z-score) × lender exposure	-0.109		-0.212		-0.083	
	(0.071)		(0.150)		(0.058)	
Leverage × lender exposure		-1.753***		-2.717***		-1.208***
		(0.506)		(0.980)		(0.419)
Lender exposure	0.036	0.708	-0.919	0.228	0.060	0.401
	(0.984)	(1.036)	(2.225)	(2.265)	(0.947)	(0.957)
Control variables	Yes					
Control variables × lender exposure	Yes					
Firm fixed effects	Yes					
Year-quarter fixed effects	Yes					
Observations	20,532	21,377	20,532	21,377	20,532	21,377
R-squared	0.874	0.895	0.874	0.895	0.874	0.895

Panel C: Supply chain diversification index and credit risk: Exposure to the financial crisis

	% # Loans reduction		Lehman exposure		ABX exposure	
VARIABLES	*Supply chain diversification index*					
	(1)	(2)	(3)	(4)	(5)	(6)
-(Z-score) × lender exposure	-0.427		-1.425**		-0.594**	
	(0.315)		(0.709)		(0.254)	
Leverage × lender exposure		-3.387		-12.416**		-5.377**
		(2.786)		(5.197)		(2.357)
Lender exposure	-0.826	-0.998	14.426	17.987*	9.034*	9.451**
	(5.639)	(5.745)	(10.042)	(10.486)	(4.710)	(4.742)
Control variables	Yes					
Control variables × lender exposure	Yes					
Firm fixed effects	Yes					
Year-quarter fixed effects	Yes					
Observations	13,877	14,369	13,877	14,369	13,877	14,369
R-squared	0.934	0.935	0.934	0.935	0.934	0.935

Panel D: Supply chain diversification ranking and credit risk: Exposure to the financial crisis

	% # Loans reduction		Lehman exposure		ABX exposure	
VARIABLES	*Supply chain diversification ranking*					
	(1)	(2)	(3)	(4)	(5)	(6)
-(Z-score) × lender exposure	-0.075		-0.249*		-0.108**	
	(0.062)		(0.137)		(0.050)	
Leverage × lender exposure		-0.682		-2.471**		-1.034**
		(0.550)		(1.027)		(0.467)
Lender exposure	-0.246	-0.340	2.300	2.966	1.478	1.501
	(1.097)	(1.111)	(1.921)	(2.014)	(0.945)	(0.951)
Control variables	Yes					
Control variables × lender exposure	Yes					
Firm fixed effects	Yes					
Year-quarter fixed effects	Yes					
Observations	13,877	14,369	13,877	14,369	13,877	14,369
R-squared	0.907	0.908	0.907	0.909	0.907	0.909

Table 8: **Markup and credit risk: Dynamic effects of exposure to the financial crisis**

Regressions of Markup on firms' -(Z-score) and Leverage that interact with the extent of lender exposures to the 2008 financial crisis in each quarter D_n, $n = -1, -2, -3, -4, +1, +2, +3, +4, +4 + (+5 — +8)$ relative to the financial crisis, from 8 quarters before it to 8 quarters after it. (The default category is from 5 to 8 quarters before the crisis.) The sample is the $2,429$ firms in Chodorow-Reich (2014). The two-year periods before and after the crisis are July 2006 to June 2008, and January 2009 to December 2010, respectively. The three measures for crisis exposure are % # Loans reduction, Lehman exposure and ABX exposure, using Chodorow-Reich 's variables in Chodorow-Reich (2014). The values of -(Z-score) and Leverage are as of the end of 2007. The firm-level control variables, as in Table 4, are fixed at the end of 2007 for the post-crisis quarters. The variable definitions are in Table 2. The last two rows show the results from F-test for joint significance of the coefficients of the interaction terms between Y and the size of LE for quarters D_n. The regressions include year-quarter and firm fixed effects. Standard errors are clustered by firm. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively.

	Panel A: $Y = -(Z - score)$			Panel B: $Y = Leverage$		
	% # Loans reduction	Lehman exposure	ABX exposure	% # Loans reduction	Lehman exposure	ABX exposure
VARIABLES	*Markup*					
	(1)	(2)	(3)	(4)	(5)	(6)
$Y \times$ Lender exposure (LE), $D_{+5\,—\,+8}$	0.074*	0.152*	0.077**	0.437	0.414	0.343
	(0.039)	(0.083)	(0.032)	(0.384)	(0.722)	(0.342)
$Y \times LE$, D_{+4}	0.071*	0.152*	0.077**	0.196	0.220	0.199
	(0.040)	(0.079)	(0.031)	(0.412)	(0.784)	(0.359)
$Y \times LE$, D_{+3}	0.130***	0.253***	0.120***	1.080***	1.620**	0.841**
	(0.038)	(0.076)	(0.030)	(0.386)	(0.747)	(0.331)
$Y \times LE$, D_{+2}	0.125***	0.233***	0.114***	1.094***	1.624**	0.894**
	(0.039)	(0.077)	(0.031)	(0.414)	(0.770)	(0.366)
$Y \times LE$, D_{+1}	0.045	0.098	0.045	1.394***	2.380***	1.201***
	(0.042)	(0.083)	(0.035)	(0.478)	(0.914)	(0.422)
$Y \times LE$, D_{-1}	0.013	0.052	0.018	0.267	0.128	0.271
	(0.026)	(0.048)	(0.021)	(0.351)	(0.611)	(0.307)
$Y \times LE$, D_{-2}	-0.007	0.013	0.008	-0.197	-0.615	-0.067
	(0.024)	(0.046)	(0.019)	(0.355)	(0.657)	(0.309)
$Y \times LE$, D_{-3}	-0.019	-0.019	-0.011	-0.413	-0.829	-0.325
	(0.022)	(0.052)	(0.018)	(0.289)	(0.672)	(0.248)
$Y \times LE$, D_{-4}	0.011	0.055	0.010	0.265	0.520	0.159
	(0.021)	(0.041)	(0.017)	(0.284)	(0.505)	(0.246)
Lender exposure, D_n	Yes					
Control variables	Yes					
Control variables $\times$ lender exposure	Yes					
Firm fixed effects	Yes					
Year-quarter fixed effects	Yes					
Observations	20,215	20,215	20,215	21,076	21,076	21,076
R-squared	0.895	0.895	0.895	0.891	0.891	0.891
F-statistic for $n = +1$ to $+4$	5.08***	4.40***	5.36***	6.18***	3.86***	4.90***
F-statistic for $n = -1$ to -4	0.66	0.79	0.64	1.58	1.08	1.26

Internet Appendix for Omitted Proofs and Additional Empirical Results

IA.1 Complete table of Panel A, Table 4

Table IA.1: **Markup and credit risk — Complete table**

This table reports the complete table of Panel A, Table 4.

VARIABLES	Markup			
	(1)	(2)	(3)	(4)
-(Z-score)	0.0038***			0.0039***
	(0.00057)			(0.00062)
Financial leverage		0.039***		
		(0.011)		
Long-term debt maturing in the next 2 years/total assets			0.073***	0.041**
			(0.018)	(0.017)
Remaining long-term leverage			0.037***	0.0081
			(0.012)	(0.012)
Tobin's Q	0.021***	0.013***	0.013***	0.022***
	(0.0020)	(0.0017)	(0.0017)	(0.0022)
Log assets	0.0096***	0.0039	0.0031	0.0089***
	(0.0030)	(0.0031)	(0.0031)	(0.0031)
Cash holdings	-0.070***	-0.098***	-0.095***	-0.061***
	(0.015)	(0.015)	(0.015)	(0.016)
Cash flow	0.91***	0.87***	0.84***	0.88***
	(0.044)	(0.042)	(0.045)	(0.046)
Asset tangibility	-0.036**	-0.032**	-0.027*	-0.037**
	(0.014)	(0.014)	(0.014)	(0.015)
Dummy variable for the top 3 industry seller	0.0082	0.0080	0.0081	0.0080
	(0.0052)	(0.0051)	(0.0052)	(0.0054)
Sales/industry sales	-0.65***	-0.55***	-0.49***	-0.60***
	(0.11)	(0.11)	(0.11)	(0.11)
Herfindahl index	0.052**	0.041*	0.038*	0.048**
	(0.022)	(0.022)	(0.020)	(0.021)
Firm fixed effects	Yes			
Year-quarter fixed effects	Yes			
Observations	571,388	583,162	504,688	477,938
R-squared	0.614	0.608	0.625	0.631

IA.2 The effect of supply chain diversification on stock returns

While abundant evidence from industry reports and academic research have shown that inventory holding can mitigate operational risk, such as fluctuations in input and output prices, as well as supply chain disruptions due to the global pandemic (e.g., Bianco and Gamba, 2019; Markou and Corsten, 2021),[34] research on the relationship between firms' supply chain management and their risk exposure is dearth. In this section, we test whether operational hedging in the form of supply chain diversification (SCD) mitigates the exposure of firms to negative economic shocks and helps firms better accommodate positive economic shocks. We estimate the following panel regression:

$$
\begin{aligned}
R_{j,k,t} = {} & b_1 \times RI_{k,t} + b_2 \times NRI_{k,t} + b_3 \times SCD_{j,k,t-2} + b_4 \times RI_{k,t} \times SCD_{j,k,t-2} \\
& + b_5 \times NRI_{k,t} \times SCD_{j,k,t-2} + b_6 \times Size_{j,k,t-2} + b_7 \times RI_{k,t} \times Size_{j,k,t-2} \\
& + b_8 \times NRI_{k,t} \times Size_{j,k,t-2} + \text{firm FE} + \text{year-quarter FE} \qquad \text{(IA.1)}
\end{aligned}
$$

$R_{j,k,t}$ is the return on the stock of customer firm j in industry k in quarter t and $RI_{k,t}$ and $NRI_{k,t}$ are, respectively, the index return and the negative index return on the firms in industry k in quarter t. We use Fama and French's 38 industry classification. $SCD_{j,k,t-2}$ is firm j's index of supply chain diversification which is either the PCA-based index of supply chain diversification that combines our three supply-chain measures or the negative average ranking of the firm (that is, the highest-ranked firm in terms of diversification has the highest value); both measures are employed in Table 3. $Size_{j,k,t-2}$ is the natural logarithm of the firm's market capitalization. The industry return is equally weighted to avoid undue weight of large firms in the industry, the estimation employs firm and quarter fixed effects, and standard errors are clustered by both firm and quarters. Importantly, industry returns are contemporaneous while the values of both SCD and $Size$ are lagged, which means that they are predetermined for the current quarter and are known to investors before setting stock prices for period t. The model thus estimates the firm's price response to market shocks given the firms supply chain arrangement prior to the shock, as well as its size beforehand.

We expect that $b_4 > 0$ and $b_5 < 0$. This means that firms with greater SCD can better cope with both positive and negative economic shocks. When the industry undergoes a positive shock and demand for resources and inputs surges, greater SCD better enables

[34] The following article documents how firms cope with the recent supply chain crisis caused by the Covid-19. "Winners and losers emerge from lingering US supply chain crisis" Financial Times, January 31, 2021. https://www.ft.com/content/76791405-3750-4965-a42a-8e0969564de1

customer firms to obtain needed resources to satisfy the growing demand. Therefore, greater SCD increases the rise in the customer firm's return in response to a rise of the industry return. On the other hand, when the industry suffers a negative shock — $RI < 0$ — greater SCD better enables customer firms to weather the storm and mitigate the negative impact of the shock. That is, greater SCD reduces the exposure of the customer firm to the negative industry shock hence $b_5 < 0$.

The model also control for the interaction terms of RI and NRI with $Size$, which is necessary because larger firms have greater supply chain diversification. We find that $corr(SCD_{j,k,t-2}, Size_{j,k,t-2})$ is 0.52 and 0.48 for SCD, that is, respectively, the PCA index of the three individual suppler chain measures and the average ranking of these individual measures. The inclusion of $RI_{k,t} \times Size_{j,k,t-2}$ and $NRI_{k,t} \times Size_{j,k,t-2}$ controls for this effect and avoids confounding of the effects of SCD and of $Size$.

The results, presented in Table IA.2, support our hypothesis. For SCD that uses the PCA index, $b_4 = 0.063$ with $t = 3.67$ and $b_5 = -0.070$ with $t = -3.10$, and for SCD that is the negative ranking (the best-diversified firm has the highest value) $b_4 = 0.375$ with $t = 3.44$ and $b_5 = -0.372$ with $t = -2.56$. These results mean that the firm's exposure to industry shocks, measured by its return's covariance with the industry return index, varies as a function of its supply chain diversification which itself changes over time. We find similar results when we replace $RI_{j,k,t}$ by the market return RM_t. Then again, $b_4 > 0$ and $b_5 < 0$, both statistically significant.

The firm's exposure to industry shocks also varies as a function of its size. We find that $b_7 < 0$ and $b_8 > 0$, both statistically significant. This means that bigger firms have smaller exposure to a rise in the industry return while they have greater exposure to a fall in the industry return. This suggests that smaller firms are nimbler and can better exploit favorable industry conditions while they have smaller exposure to shocks when the industry return falls.

The effect of $SCD_{j,k,t-2}$ and $Size_{j,k,t-2}$ on expected return two quarters ahead is negative and significant: According to Column (1) of Table IA.2, $b_3 = -0.006$ with $t = -2.69$ and $b_6 = -0.066$ with $t = -7.01$. Qualitatively similar results also hold according to Column (2). The negative effect of Size is well known. The new result here is that greater supply chain diversification predicts a lower expected return. This means that the supply chain risk is priced. After controlling for the effect of SDC on the firm's systematic risk, which varies with SCD, expected return is lower for firms with greater SCD. This indicates a benefit that the firm derives from operational hedging in the form of supply chain diversification on the firm's cost of equity capital. Notably, the model includes firm fixed effects which controls for omitted variables that may affect its expected return.

We replicate the same analysis for another means of operational hedging, replacing $SCD_{j,k,t-2}$ by $INV_{j,k,t-2}$, the ratio of end-of-quarter inventory to the quarterly sales, all lagged by two quarters. We find in this model that b_3 is -0.025 with $t = -9.04$, which means that operational hedging in the form of inventory hoarding is beneficial by lowering the expected return and the firm's cost of capital.[35] We find, however, that b_4 and b_5 are statistically insignificant meaning that the covariance of the firm's return with industry shocks is not affected by inventory. Whereas operational hedging through supply chain diversification is planned, the quarterly level of the inventory-to-sales ratio, which we use in the estimation, is partly planned and partly a realization of a random shock to sales or to production compared to plans. This could explain the lower explanatory power of the lagged level of inventory in interaction with market returns; it is nonetheless negative and significant in explaining the expected return. (The tabulated results are available upon request.) The extent to which firms rely on a relative basis between supply chain diversification and inventory in their operational hedging mix is an interesting avenue for future research.

As a robustness check, we replace the industry return with the quarterly changes of industrial production in manufacturing sector, as an alternative measure of industry shocks. The results are qualitatively similar.

[INSERT Table IA.2.]

[35] Using natural logarithm of one plus the ratio of end-of-quarter inventory to the quarterly sales, lagged by two quarters, yields $b_3 = -0.053$ with $t = -8.70$.

Table IA.2: **Stock return, industry shocks and supply chain diversification**

Estimation of the relationship between Stock return, and Industry stock returns or Changes in industrial production, conditional on Supply chain diversification. In Panel A, we use Fama-French 38 industry return where the industry return is matched to the industry in which the firm operates, and in Panel B, we use quarterly changes of industrial production in manufacturing sector. The data are quarterly over the period 2003-2020. We lag supply chain diversification (SCD) and natural logarithm of market capitalization ($Size$) by two quarters. For SCD we use two variables as in Table 3: the SCD index and the (negative) of SCD ranking. The sample selection is as in Table 2. The regressions include year-quarter and firm fixed effects. Standard errors are clustered at firm and year-quarter levels. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively.

Panel A: Fama-French 38 industry return

VARIABLES	*Stock return*	
	(1)	(2)
FF38 industry return	2.106***	2.263***
	(0.114)	(0.156)
Negative FF38 industry return	-0.922***	-1.055***
	(0.173)	(0.228)
Supply chain diversification index	-0.006***	
	(0.002)	
Supply chain diversification ranking		-0.033***
		(0.012)
FF38 return × SCD index	0.063***	
	(0.017)	
Negative FF38 return × SCD index	-0.070***	
	(0.023)	
FF38 return × SCD ranking		0.375***
		(0.109)
Negative FF38 return × SCD ranking		-0.372**
		(0.145)
Size	-0.066***	-0.066***
	(0.009)	(0.009)
FF38 return × size	-0.180***	-0.176***
	(0.017)	(0.017)
Negative FF38 return × size	0.144***	0.137***
	(0.026)	(0.025)
Firm fixed effects	Yes	
Year-quarter fixed effects	Yes	
Observations	102,574	102,574
R-squared	0.296	0.296

Panel B: Quarterly changes of industrial production in manufacturing sector

VARIABLES	*Stock return*	
	(1)	(2)
Supply chain diversification index	-0.006***	
	(0.002)	
Supply chain diversification ranking		-0.038***
		(0.011)
Qtr. change in ind. production manu. × SCD index	0.429**	
	(0.206)	
Negative qtr. change in ind. production manu. × SCD index	-0.613***	
	(0.229)	
Qtr. change in ind. production manu. × SCD ranking		2.492**
		(1.245)
Negative qtr. change in ind. production manu. × SCD ranking		-3.664**
		(1.391)
Size	-0.077***	-0.077***
	(0.013)	(0.013)
Qtr. change in ind. production manu. × size	-0.856*	-0.815*
	(0.450)	(0.439)
Negative qtr. change in ind. production manu. × size	1.032*	0.981*
	(0.524)	(0.514)
Firm fixed effects	Yes	
Year-quarter fixed effects	Yes	
Observations	102,574	102,574
R-squared	0.244	0.244

IA.3 Second-order condition in benchmark case ($F = 0$)

The second-order derivative of $\bar{E}$ with respect to i is:

$$\frac{\partial^2 \bar{E}}{\partial i^2} = -K''(I+i) - \frac{\lambda x_2}{I^2} \frac{g'(u_O) - g(u_O)\frac{\delta''(u_O)}{\delta'(u_O)}}{[\delta'(u_O)]^2} < 0 \tag{IA.2}$$

Since $\delta(u)$ is decreasing and convex in u, $\frac{\partial^2 \bar{E}}{\partial i^2}$ is always negative if the production commitment I is sufficiently high. In other words, the objective function $\bar{E}$ is concave in i. Thus, $\bar{i}$ is the unique optimal solution that maximizes the equity value (2.5).

IA.4 Optimal hedging policy when $u_F \geq u_O$

We begin this subsection by proving Lemma 2.1. First, we show that i^* that satisfies the first-order condition (2.9) is the unique optimal solution for the maximization problem when $u_F > u_O$. Define $S = p - K'(I+i) - V(u_F, i)h(u_F)K'(I+i)$. Taking the derivative of S with respect to i:

$$\frac{\partial S}{\partial i} = -\left[\begin{array}{c} K''(I+i) + \frac{\partial V(u_F,i)}{\partial i} h(u_F)K'(I+i) \\ +V(u_F,i)\frac{\partial h(u_F)}{\partial u_F}\frac{\partial u_F}{\partial i}K'(I+i) + V(u_F,i)h(u_F)\frac{\partial^2 u_F}{\partial i^2} \end{array} \right] \tag{IA.3}$$

$$\frac{\partial V(u_F, i)}{\partial i} = p[1 - \delta'(u_F)IK'(I+i)] > 0 \tag{IA.4}$$

and

$$\frac{\partial^2 u_F}{\partial i^2} = K''(I+i) > 0 \tag{IA.5}$$

Using these quantities,

$$\frac{\partial S}{\partial i} = -\left[\begin{array}{c} K''(I+i) + p[1 - \delta'(u_F)IK'(I+i)]h(u_F)K'(I+i) \\ +V(u_F,i)\frac{\partial h(u_F)}{\partial u_F}[K'(I+i)]^2 + V(u_F,i)h(u_F)K''(I+i) \end{array} \right] \tag{IA.6}$$

$\frac{\partial S}{\partial i}$ is smaller than zero. Thus, the second-order condition for maximization $[1-G(u_F)]\frac{\partial S}{\partial i}$ at $i = i^*$ is smaller than zero. By the first-order condition (2.9), $S = 0$ if $i = i^*$. Since $\frac{\partial S}{\partial i} < 0$, we have $S > 0$ if $i < i^*$ and $S < 0$ if $i > i^*$. Since $\frac{\partial}{\partial i}E = [1 - G(u_F)]S$, E increases in i for $i < i^*$ and decreases in i for $i > i^*$. Therefore i^* is the unique optimal solution to the maximization problem.

Now we prove that Assumption 2.2 is sufficient condition that guarantees a positive interior solution i^* and $D(i^*, \bar{F}) > 0$ when $\bar{F}$ is sufficiently large. Denote $\underline{i}$ such that $p - K'(I + \underline{i}) = (p(I + \underline{i}) + x_2)\alpha K'(I + \underline{i})$. Notice that $\underline{i}$ must be strictly greater than zero. This is because the left hand-side of the above equation decreases with i, the right hand-side increases with i, and left hand-side is strictly greater than the right hand-side when $i = 0$ by Assumption 2.2, since $K(I + i)$ is convex in i. For any $\bar{F} > 0$, the right hand-side of the first-order condition (2.10) when $i = \underline{i}$ is $V(u_F, \underline{i})\alpha K'(I + \underline{i})$, which is smaller than $(p(I + \underline{i}) + x_2)\alpha K'(I + \underline{i}) = p - K'(I + \underline{i})$. The left hand-side of the first-order condition (2.10) decreases with i. The right hand-side of the first-order condition (2.10) increases with i. This is because u_F increases with i and $\delta(u)$ decreases with u. Consequently, $(1 - \delta(u_F))$ increases with i. $K'(I+i)$ increases with i because the convexity of K in i. So the optimal i^* that satisfies the first-order condition (2.10) must be strict greater than $\underline{i}$. Denote $\bar{F}_M$ such that $D(\underline{i}, \bar{F}_M) = 0$. Then for any $\bar{F} \geq \bar{F}_M$, we must have $D(i^*(\bar{F}), \bar{F}) > D(\underline{i}, \bar{F}) > 0$. This is because $D(\bar{F}, i)$ increases in $\bar{F}$ and i, and $i^*(\bar{F}) > \underline{i}$. Thus, we have proved that for $\bar{F} > \bar{F}_M$, the first-order condition (2.10) admits a positive interior solution i^* and the financial default boundary u_F is greater than the operational default boundary u_O when the firm chooses the optimal hedging policy i^*. Since we have proved that the first-order condition (2.10) is also the sufficient condition for the solution of the constrained maximization problem subject to $D(i, \bar{F}) > 0$, we have proved Lemma 2.1.

In what follows, we proof Lemma 2.2: Notice that the optimal hedging policy i^* and the associated financial default boundary u_F are all functions of $\bar{F}$. The firm's optimal operational hedging policy i^* decreases in $\bar{F}$. Define $M(i^*(\bar{F}), \bar{F}) \equiv E(i^*(\bar{F}), \bar{F})$ the value function under optimal hedging policy i^*. By the first-order condition, $\frac{\partial M}{\partial i^*} = 0$. Differentiating both sides with respect to $\bar{F}$:

$$\frac{\partial^2 M}{\partial i^{*2}} \frac{\partial i^*}{\partial \bar{F}} + \frac{\partial M}{\partial i \partial \bar{F}} = 0 \tag{IA.7}$$

From equation (IA.7) we get $\frac{\partial i^*}{\partial \bar{F}} = -\frac{\partial^2 M}{\partial i^* \partial \bar{F}} / \frac{\partial^2 M}{\partial i^{*2}}$. Since $\frac{\partial^2 M}{\partial i^{*2}} < 0$ by the second-order condition, so the sign of $\frac{\partial i^*}{\partial \bar{F}}$ is the same as the sign of $\frac{\partial M}{\partial i^* \partial \bar{F}}$.

$$\begin{aligned} \frac{\partial^2 M}{\partial i^* \partial \bar{F}} &= [1 - G(u_F)] \left[pI\delta'(u_F) \frac{\partial u_F}{\partial \bar{F}} h(u_F) K'(I + i^*) - V(u_F, i^*) \frac{\partial h(u_F)}{\partial u_F} \frac{\partial u_F}{\partial \bar{F}} K'(I + i) \right] \\ &= [1 - G(u_F)] \left[pI\delta'(u_F) h(u_F) K'(I + i^*) - V(u_F, i^*) \frac{\partial h(u_F)}{\partial u_F} K'(I + i) \right] \end{aligned} \tag{IA.8}$$

Since u follows a exponential distribution, $\frac{\partial h(u_F)}{\partial u_F} = 0$. Thus, Equation (IA.8) is smaller than zero. Therefore, $\frac{\partial i^*}{\partial \bar{F}} < 0$.

IA.5 Optimal hedging policy when $u_F < u_O$

We begin this subsection by proving Lemma 2.3. First, we show that $\hat{i}^*$ that satisfies the first-order condition (2.12) is the unique optimal solution for the maximization problem. Define $\hat{S} = p - K'(I+i) - [V(u_F, i) - \lambda x_2]h(u_F)K'(I+i) - \frac{\lambda x_2 g(u_O)}{1-G(u_F)}\frac{\partial u_O}{\partial i}$. Taking the derivative of $\hat{S}$ with respect to i:

$$\frac{\partial \hat{S}}{\partial i} = -\left[\begin{array}{c} K''(I+i) + \frac{\partial V(u_F,i)}{\partial i}h(u_F)K'(I+i) + [V(u_F,i) - \lambda x_2]\frac{\partial h(u_F)}{\partial u_F}\frac{\partial u_F}{\partial i}K'(I+i) \\ +[V(u_F,i) - \lambda x_2]h(u_F)\frac{\partial^2 u_F}{\partial i^2} + \lambda x_2 \frac{\partial}{\partial i}\left[\frac{g(u_O)}{[1-G(u_F)]I\delta'(u_O)}\right] \end{array}\right] \tag{IA.9}$$

$$\frac{\partial}{\partial i}\left[\frac{g(u_O)}{[1-G(u_F)]I\delta'(u_O)}\right] = \left[\frac{g'(u_O)\delta'(u_O) - g(u_O)\delta''(u_O)}{[1-G(u_F)][\delta'(u_O)]^2 I} + \frac{g(u_F)K'(I+i)g(u_O)}{[1-G(u_F)]^2}\right]\frac{1}{I\delta'(u_O)} \tag{IA.10}$$

The absolute value of (IA.10) is small if the production commitment I is sufficiently high and $\frac{K'(I+\bar{i})}{I}$ is sufficiently low. In the numerical analysis, we assume that $K(I+i)$ is of quadratic form, $K(I+i) = \kappa(I+i)^2$, where $\kappa > 0$, which is standard in the investment literature. Then $\frac{K'(I+\bar{i})}{I}$ is sufficiently low if κ is sufficiently small. Using quantities (IA.4), (IA.5) and (IA.10), $\frac{\partial \hat{S}}{\partial i}$ is

$$\frac{\partial \hat{S}}{\partial i} = -\left[\begin{array}{c} K''(I+i) + p[1 - \delta'(u_F)IK'(I+i)]h(u_F)K'(I+i) \\ +[V(u_F,i) - \lambda x_2]\frac{\partial h(u_F)}{\partial u_F}[K'(I+i)]^2 + [V(u_F,i) - \lambda x_2]h(u_F)K''(I+i) \\ +\lambda x_2\left[\frac{g'(u_O)\delta'(u_O) - g(u_O)\delta''(u_O)}{[1-G(u_F)][\delta'(u_O)]^2 I} + \frac{g(u_F)K'(I+i)g(u_O)}{[1-G(u_F)]^2}\right]\frac{1}{I\delta'(u_O)} \end{array}\right] \tag{IA.11}$$

$\frac{\partial \hat{S}}{\partial i}$ is always smaller than zero, thus, the second-order condition for maximization $[1 - G(u_F)]\frac{\partial \hat{S}}{\partial i}$ at $i = \hat{i}^*$ is smaller than zero. By the first-order condition (2.12), $\hat{S} = 0$ if $i = \hat{i}^*$. Since $\frac{\partial \hat{S}}{\partial i} < 0$, we have $\hat{S} > 0$ if $i < \hat{i}^*$ and $\hat{S} < 0$ if $i > \hat{i}^*$. Since $\frac{\partial}{\partial i}\hat{E} = [1 - G(u_F)]\hat{S}$, $\hat{E}$ increases in i for $i < \hat{i}^*$ and decreases in i for $i > \hat{i}^*$. Therefore $\hat{i}^*$ is the unique optimal solution to the maximization problem.

Now we prove Lemma 2.4: $\hat{i}^* > i^*$. i^* satisfies the first-order condition (2.9):

$$\begin{aligned} p - K'(I+i^*) &= V(u_F, i^*)h(u_F)K'(I+i^*) \\ &> V(u_F, i^*)h(u_F)K'(I+i^*) - \lambda x_2 h(u_F)K'(I+i^*) + \frac{\lambda x_2 g(u_O)}{[1-G(u_F)]I\delta'(u_O)} \end{aligned} \tag{IA.12}$$

The inequality holds because $\lambda x_2 h(u_F)K'(I+i^*) > 0$ and $\frac{\lambda x_2 g(u_O)}{[1-G(u_F)]I\delta'(u_O)} < 0$. Now taking derivative of both sides of the first-order condition in $u_O > u_F$ case, (2.12), with respect to

i. The derivative of the left-hand side is $-K''(I+i) < 0$. The derivative of the right-hand side is

$$p[1-\delta'(u_F)IK'(I+i)]h(u_F)K'(I+i) + [V(u_F,i)-\lambda x_2]\frac{\partial h(u_F)}{\partial u_F}[K'(I+i)]^2$$
$$+ [V(u_F,i)-\lambda x_2]h(u_F)K''(I+i)$$
$$+ \lambda x_2\left[\frac{g'(u_O)\delta'(u_O)-g(u_O)\delta''(u_O)}{[1-G(u_F)][\delta'(u_O)]^2 I} + \frac{g(u_F)K'(I+i)g(u_O)}{[1-G(u_F)]^2}\right]\frac{1}{I\delta'(u_O)} \tag{IA.13}$$

The quantity (IA.13) is always greater than zero if the production commitment I is sufficiently high and $\frac{K'(I+\bar{i})}{I}$ is sufficiently low. Thus the left-hand side of Equation (2.12) decreases in i and the right-hand side of Equation (2.12) increases in i. Since $\hat{i}^*$ satisfies the first-order condition in $u_O > u_F$ case, (2.12). We must have $\hat{i}^* > i^*$.

In what follows, we prove Lemma 2.5: the firm's optimal operational hedging policy $\hat{i}^*$ decreases in $\bar{F}$. Define $\hat{M}(\hat{i}^*(\bar{F}),\bar{F}) \equiv E(\hat{i}^*(\bar{F}),\bar{F})$ the value function under optimal hedging policy $\hat{i}^*$. Similar to the $u_F > u_O$ case, $\frac{\partial \hat{i}^*}{\partial \bar{F}} = -\frac{\partial^2 \hat{M}}{\partial \hat{i}^* \partial \bar{F}} / \frac{\partial^2 \hat{M}}{\partial \hat{i}^{*2}}$. Since $\frac{\partial^2 \hat{M}}{\partial \hat{i}^{*2}} < 0$ by the second-order condition, so the sign of $\frac{\partial \hat{i}^*}{\partial \bar{F}}$ is the same as the sign of $\frac{\partial \hat{M}}{\partial \hat{i}^* \partial \bar{F}}$.

$$\frac{\partial^2 \hat{M}}{\partial \hat{i}^* \partial \bar{F}} = [1-G(u_F)]\left[\begin{array}{c} pI\delta'(u_F)\frac{\partial u_F}{\partial \bar{F}}h(u_F)K'(I+\hat{i}^*) - [V(u_F,\hat{i}^*)-\lambda x_2]\frac{\partial h(u_F)}{\partial u_F}\frac{\partial u_F}{\partial \bar{F}}K'(I+i) \\ -\frac{\lambda x_2}{I}\frac{g(u_O)g(u_F)}{[1-G(u_F)]^2\delta'(u_O)}\frac{\partial u_F}{\partial \bar{F}} \end{array}\right]$$
$$= [1-G(u_F)]\left[\begin{array}{c} pI\delta'(u_F)h(u_F)K'(I+i^*) - [V(u_F,i^*)-\lambda x_2]\frac{\partial h(u_F)}{\partial u_F}K'(I+i) \\ -\frac{\lambda x_2}{I}\frac{g(u_O)g(u_F)}{[1-G(u_F)]^2\delta'(u_O)} \end{array}\right] \tag{IA.14}$$

Since u follows an exponential distribution, $\frac{\partial h(u_F)}{\partial u_F} = 0$. Thus, Equation (IA.14) is always smaller than zero if the production commitment I is sufficiently high. Therefore, $\frac{\partial i^*}{\partial \bar{F}} < 0$ if the production commitment I is sufficiently high.

IA.6 Optimal operational hedging policy and net debt $\bar{F}$

First of all, $\bar{i}$ in Appendix IA.3 is the optimal equity-maximizing hedging policy given the inherited net short-term debt level $\bar{F}$ is sufficiently low, i.e., $\bar{F} \leq \bar{F}_{fb}$. $\bar{F}_{fb}$ is such that $\bar{F}_{fb} + K(I+\bar{i}) = 0$, i.e., $\bar{F}_{fb}$ is the maximal net debt level such that the firm is able to pay back the debt at date-1 it chooses the maximal optimal hedging policy $\bar{i}$ that maximizes the unlevered firm value. When $\bar{F} > \bar{F}_{fb}$, the firm has to choose the optimal hedging policy i that balances the concerns over financial and operational default, which we elaborate on below.

Notice that $D(i, \bar{F})$ is continuously differentiable in both i and $\bar{F}$ with partial derivatives:

$$\frac{\partial D}{\partial i} = K'(I+i) - \frac{1}{I\delta'(u_O)} \ , \tag{IA.15a}$$

$$\frac{\partial D}{\partial \bar{F}} = 1 \ . \tag{IA.15b}$$

Notice that $\frac{\partial D}{\partial i} > 0$ because $K'(I+i) > 0$ and $\delta'(u) < 0$ by assumption. The following lemma is for technical purpose. It facilitates our proof that both $D^*(\bar{F}) = 0$ and $\hat{D}^*(\bar{F}) = 0$ has unique solutions, which we denote as $\bar{F}_0$ and $\bar{F}_1$, respectively.

Lemma IA.1.

$$\frac{dD^*}{d\bar{F}} > 0 \ \textit{if} \ u_F(i^*) \geq u_O(i^*) \tag{IA.16a}$$

$$\frac{d\hat{D}^*}{d\bar{F}} > 0 \ \textit{if} \ u_F(\hat{i}^*) \geq u_O(\hat{i}^*) \tag{IA.16b}$$

Proof. First we prove the following inequality:

$$\frac{dD^*}{d\bar{F}} = \frac{\partial D^*}{\partial \bar{F}} + \frac{\partial D^*}{\partial i^*}\frac{\partial i^*}{\partial \bar{F}} > 0 \tag{IA.17}$$

Using Equations (IA.15a) and (IA.15b) Inequality (IA.17) is equivalent to

$$\left[K'(I+i^*) - \frac{1}{I\delta'(u_O)}\right]\left(-\frac{\partial i^*}{\partial \bar{F}}\right) < 1 \tag{IA.18}$$

From Appendix IA.4, $\frac{\partial i^*}{\partial \bar{F}} = -\frac{\partial^2 M}{\partial i^* \partial \bar{F}} / \frac{\partial^2 M}{\partial i^{*2}}$. $\frac{\partial^2 M}{\partial i^* \partial \bar{F}}$ is given by Equation (IA.8). $\frac{\partial^2 M}{\partial i^{*2}}$ is given by $[1 - G(u_F)]\frac{\partial S}{\partial i^*}$ where $\frac{\partial S}{\partial i^*}$ is given by Equation (IA.6) at $i = i^*$. Thus, Inequality (IA.18) is equivalent to

$$\frac{V(u_F,i^*)\frac{\partial h(u_F)}{\partial u_F}K'(I+i^*) - pI\delta'(u_F)h(u_F)K'(I+i^*)}{\begin{bmatrix} K''(I+i^*) + p[1-\delta'(u_F)IK'(I+i^*)]h(u_F)K'(I+i^*) \\ +V(u_F,i^*)\frac{\partial h(u_F)}{\partial u_F}[K'(I+i^*)]^2 + V(u_F,i^*)h(u_F)K''(I+i^*) \end{bmatrix}} \frac{1 - I\delta'(u_O)K'(I+i^*)}{-I\delta'(u_O)} < 1 \tag{IA.19}$$

Algebraic simplification shows that the above inequality is equivalent to

$$
\begin{aligned}
&V(u_F,i^*)\frac{\partial h(u_F)}{\partial u_F}K'(I+i^*)+pI\left[\delta'(u_O)-\delta'(u_F)\right]h(u_F)K'(I+i^*)\\
&<\left[1+V(u_F,i^*)h(u_F)\right]K''(I+i^*)\left[-I\delta'(u_O)\right] \qquad \text{(IA.20)}
\end{aligned}
$$

Since u follows a exponential distribution, $\frac{\partial h(u)}{\partial u}=0$ and the first term of the left-hand side of Inequality (IA.20) is equal to zero. the second term on the left-hand side is (weakly) smaller than zero if $u_F \geq u_O$ because $\delta(u)$ is convex in u. Therefore the left-hand side of Inequality (IA.20) is (weakly) smaller than zero. The right-hand side of Inequality (IA.20) is strictly greater than zero. Therefore, Inequality (IA.20) holds and $\frac{dD^*}{d\bar{F}}>0$.

Now we prove the following inequality:

$$
\frac{d\hat{D}^*}{d\bar{F}}=\frac{\partial\hat{D}^*}{\partial\bar{F}}+\frac{\partial\hat{D}^*}{\partial\hat{i}^*}\frac{\partial\hat{i}^*}{\partial\bar{F}}>0 \qquad \text{(IA.21)}
$$

Inequality (IA.17) is equivalent to

$$
\left[K'(I+\hat{i}^*)-\frac{1}{I\delta'(u_O)}\right]\left(-\frac{\partial\hat{i}^*}{\partial\bar{F}}\right)<1 \qquad \text{(IA.22)}
$$

From Appendix IA.5, $\frac{\partial\hat{i}^*}{\partial\bar{F}}=-\frac{\partial^2\hat{M}}{\partial\hat{i}^*\partial\bar{F}}/\frac{\partial^2\hat{M}}{\partial\hat{i}^{*2}}$. $\frac{\partial^2\hat{M}}{\partial i^*\partial\bar{F}}$ is given by Equation (IA.14). $\frac{\partial^2\hat{M}}{\partial\hat{i}^{*2}}$ is given by $[1-G(u_F)]\frac{\partial\hat{S}}{\partial\hat{i}^*}$ where $\frac{\partial\hat{S}}{\partial\hat{i}^*}$ is given by Equation (IA.11) at $i=\hat{i}^*$. Thus, Inequality (IA.22) is equivalent to

$$
\frac{\begin{bmatrix}[V(u_F,\hat{i}^*)-\lambda x_2]\frac{\partial h(u_F)}{\partial u_F}K'(I+\hat{i}^*)\\ -pI\delta'(u_F)h(u_F)K'(I+\hat{i}^*)\\ +\frac{\lambda x_2}{I}\frac{g(u_O)g(u_F)}{[1-G(u_F)]^2\delta'(u_O)}\end{bmatrix}}{\begin{bmatrix}K''(I+\hat{i}^*)+p[1-\delta'(u_F)IK'(I+\hat{i}^*)]h(u_F)K'(I+\hat{i}^*)\\ +[V(u_F,\hat{i}^*)-\lambda x_2]\frac{\partial h(u_F)}{\partial u_F}[K'(I+\hat{i}^*)]^2\\ +[V(u_F,\hat{i}^*)-\lambda x_2]h(u_F)K''(I+\hat{i}^*)\\ +\lambda x_2\left[\frac{g'(u_O)\delta'(u_O)-g(u_O)\delta''(u_O)}{[1-G(u_F)][\delta'(u_O)]^2I}+\frac{g(u_F)K'(I+\hat{i}^*)g(u_O)}{[1-G(u_F)]^2}\right]\frac{1}{I\delta'(u_O)}\end{bmatrix}}\frac{1-I\delta'(u_O)K'(I+\hat{i}^*)}{-I\delta'(u_O)}<1 \qquad \text{(IA.23)}
$$

Algebraic simplification shows that the above inequality is equivalent to

$$[V(u_F,\hat{i}^*)-\lambda x_2]\frac{\partial h(u_F)}{\partial u_F}K'(I+\hat{i}^*)+pI\left[\delta'(u_O)-\delta'(u_F)\right]h(u_F)K'(I+\hat{i}^*)+\frac{\lambda x_2}{I}\frac{g(u_O)g(u_F)}{[1-G(u_F)]^2\delta'(u_O)}$$
$$<\left[1+[V(u_F,\hat{i}^*)-\lambda x_2]h(u_F)\right]K''(I+\hat{i}^*)\left[-I\delta'(u_O)\right]-\lambda x_2\frac{g'(u_O)\delta'(u_O)-g(u_O)\delta''(u_O)}{[1-G(u_F)][\delta'(u_O)]^2 I} \quad \text{(IA.24)}$$

Since u follows a exponential distribution, $\frac{\partial h(u)}{\partial u}=0$ and the first term of the left-hand side of Inequality (IA.24) is equal to zero. the second term on the left-hand side is (weakly) smaller than zero if $u_F \geq u_O$ because $\delta(u)$ is convex in u. The first term of the right-hand side of Inequality (IA.24) is strictly greater than zero. Therefore, to show that Inequality (IA.24) holds, we need to show that:

$$\frac{\lambda x_2}{I}\frac{g(u_O)g(u_F)}{[1-G(u_F)]^2\delta'(u_O)}<-\lambda x_2\frac{g'(u_O)\delta'(u_O)-g(u_O)\delta''(u_O)}{[1-G(u_F)][\delta'(u_O)]^2 I} \quad \text{(IA.25)}$$

Or, equivalently,

$$\frac{\lambda x_2}{I}\frac{g(u_O)g(u_F)}{[1-G(u_F)]^2\delta'(u_O)}+\lambda x_2\frac{g'(u_O)\delta'(u_O)-g(u_O)\delta''(u_O)}{[1-G(u_F)][\delta'(u_O)]^2 I}<0$$
$$\Leftrightarrow \frac{\lambda x_2}{I[1-G(u_F)]\delta'(u_O)}\left[\frac{g(u_O)g(u_F)}{[1-G(u_F)]}+\frac{g'(u_O)\delta'(u_O)-g(u_O)\delta''(u_O)}{\delta'(u_O)}\right]<0$$
$$\Leftrightarrow \frac{g(u_O)g(u_F)}{[1-G(u_F)]}+\frac{g'(u_O)\delta'(u_O)-g(u_O)\delta''(u_O)}{\delta'(u_O)}>0 \quad \text{(IA.26)}$$

Since $g(u)=\alpha\exp(-\alpha u)$, $\alpha g(u)=-g'(u)$, and $\frac{g(u_F)}{[1-G(u_F)]}=\alpha$, the inequality (IA.26) is equivalent to

$$\frac{\delta''(u_O)}{\delta'(u_O)}<0 \quad \text{(IA.27)}$$

which always holds since $\delta(u)$ decreases and convex in u by assumption. Therefore, $\frac{d\hat{D}^*}{d\bar{F}}>0$. Q.E.D.

Now we prove Proposition 2.1. First, i^* and $\hat{i}^*$ are continuously differentiable in $\bar{F}$ and $D(i,\bar{F})$ is continuously differentiable in both i and f. It follows that $D^*(\bar{F})$ and $\hat{D}^*(\bar{F})$ are continuously differentiable, thus continuous in $\bar{F}$.

Secondly, from Section 2.4 and Section 2.5, we know that u_F is greater than u_O, i.e., $D^*,\hat{D}^*>0$ when $\bar{F}$ is sufficiently high, i.e., $\bar{F}\geq\bar{F}_M$. To see this, from Lemma 2.1,$D^*>0$ if $\bar{F}\geq\bar{F}_M$. From Lemma 2.4, for a given $\bar{F}$, $\hat{i}^*>i^*$. Since $D(i,\bar{F})$ increases in i, $\hat{D}^*>0$ when $\bar{F}\geq\bar{F}_M$. On the other hand, if $F=0$, $u_F=0$, which is always lower than u_O. Since $D^*(\bar{F})$

and $\hat{D}^*(\bar{F})$ are continuous in $\bar{F}$, $D^*, \hat{D}^* < 0$ for all $\bar{F}$ that is sufficiently low. Again by the continuity of $D^*(\bar{F})$ and $\hat{D}^*(\bar{F})$ in $\bar{F}$, there must exist $\bar{F}_0$ and $\bar{F}_1$ such that $\hat{D}^*(\bar{F}_0) = 0$ and $D^*(\bar{F}_1) = 0$. By Lemma IA.1, $\frac{d\hat{D}^*}{d\bar{F}} > 0$ whenever $\hat{D}^* \geq 0$ and $\frac{dD^*}{d\bar{F}} > 0$ whenever $D^* \geq 0$. It follows that $\bar{F}_0$ and $\bar{F}_1$ are unique. Moreover, $\hat{D}^* < 0$ for all $\bar{F} < \bar{F}_0$ and $\hat{D}^* > 0$ for all $\bar{F} > \bar{F}_0$. Similarly, $D^* < 0$ for all $\bar{F} < \bar{F}_1$ and $D^* > 0$ for all $\bar{F} > \bar{F}_1$.

From Lemma 2.4, $\hat{i}^* > i^*$ for any given $\bar{F}$. At $\bar{F} = \bar{F}_1$, $D^*(\bar{F}_1) = 0$. Since $\frac{\partial D}{\partial i} > 0$, we must have $\hat{D}^*(\bar{F}_1) = D(\hat{i}^*(\bar{F}_1), \bar{F}_1) > 0$. Thus, $\bar{F}_1 > \bar{F}_0$.

To conserve space, we omit the argument $\bar{F}$ in i^*, $\tilde{i}$ and $\hat{i}^*$. If $\bar{F} \leq \bar{F}_0$, then $D^* < 0$ and $\hat{D}^* \leq 0$. Thus, maximizing the equity value subject to $u_F \leq u_O$ will yield the optimal operational hedging policy $\hat{i}^*$. Meanwhile, maximizing the equity value subject to $u_F \geq u_O$ will yield a corner solution $\tilde{i} > i^*$, in which $\tilde{i}$ is such that $D(\tilde{i}, \bar{F}) = 0$. Indeed, for a given $\bar{F}$ in this region, the feasible set of i for the maximization problem of the equity value subject to $u_F \geq u_O$, if not empty, is $i \geq \tilde{i} > i^*$. From Appendix IA.4, the equity value E decreases in i for $i > i^*$. Since $\tilde{i}$ is also feasible for the maximization problem of the equity value subject to $u_F \leq u_O$ and $\hat{E} = E$ when $i = \tilde{i}$, $\tilde{i}$ must yield a lower expected payoff for the shareholders, compared with $\hat{i}^*$. Thus, the optimal operational hedging policy is $\hat{i}^*$.

If $\bar{F}_0 < \bar{F} < \bar{F}_1$, then $D^* < 0$ and $\hat{D}^* > 0$. Thus, maximizing the equity value subject to $u_F \leq u_O$ or subject to $u_F \geq u_O$ will yield the same corner solution $\tilde{i}$, in which $\tilde{i}$ is such that $D(\tilde{i}, \bar{F}) = 0$. This is because, for a given $\bar{F}$ in this region, the feasible set i for the maximization problem of the equity value subject to $u_F \geq u_O$ is $i \geq \tilde{i} > i^*$, and from Appendix IA.4, equity value E decreases in i for $i > i^*$. Meanwhile, the feasible set i for the maximization problem of the equity value subject to $u_F \leq u_O$ is $i \leq \tilde{i} < \hat{i}^*$ and from Appendix IA.5, $\hat{E}$ increases in i for $i < i^*$. Thus, the optimal operational hedging policy is $\tilde{i}$.

If $\bar{F} \geq \bar{F}_1$, then $D^* \geq 0$ and $\hat{D}^* > 0$. Thus, maximizing the equity value subject to $u_F \geq u_O$ will yield the optimal operational hedging policy i^*. Meanwhile, maximizing the equity value subject to $u_F < u_O$ will yield a corner solution $\tilde{i} < \hat{i}^*$. Indeed, for a given $\bar{F}$ in this region, the feasible set of i for the maximization problem of the equity value subject to $u_F \leq u_O$, if not empty, is $i \leq \tilde{i} < \hat{i}^*$ and from Appendix IA.5, $\hat{E}$ increases in i for $i < \hat{i}^*$. Since $\tilde{i}$ is also feasible for the maximization problem of the equity value subject to $u_F \geq u_O$ and $\hat{E} = E$ when $i = \tilde{i}$, $\tilde{i}$ must yield a lower expected payoff for the shareholders, compared with i^*. Thus, the optimal operational hedging policy is i^*.

Now we prove Proposition 2.2. From Proposition 2.1 and Lemma 2.2, when $\bar{F} > \bar{F}_1$, $i^{**} = i^*$ and thus decreases in $\bar{F}$. Similarly, from Proposition 2.1 and Lemma 2.5, when $\bar{F} < \bar{F}_0$, $i^{**} = \hat{i}^*$ and thus decreases in $\bar{F}$. Moreover, $\frac{\partial \tilde{i}}{\partial \bar{F}} = -\frac{\partial D}{\partial \bar{F}} / \frac{\partial D}{\partial \tilde{i}}$. Since both partial derivatives on the right-hand side are positive from Inequalities (IA.15a) and (IA.15b), $\frac{\partial \tilde{i}}{\partial \bar{F}} < 0$. When

$\bar{F}_0 < \bar{F} < \bar{F}_1$, $i^{**} = \tilde{i}$ and thus decreases in $\bar{F}$. Lastly, at $\bar{F} = \bar{F}_1$, since $D^* = 0$, $i^* = \tilde{i}$, so $i^{**} = i^* = \tilde{i}$ at $\bar{F} = \bar{F}_1$ and thus is continuous in $\bar{F}$ at $\bar{F} = \bar{F}_1$. Similarly, at $\bar{F} = \bar{F}_0$, since $\hat{D}^* = 0$, $\hat{i}^* = \tilde{i}$, so $i^{**} = \hat{i}^* = \tilde{i}$ at $\bar{F} = \bar{F}_0$ and thus is continuous in $\bar{F}$ at $\bar{F} = \bar{F}_0$. Therefore, i^{**} decreases in $\bar{F}$.