# 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 (bankruptcy) risk, and spending on operational hedging to mitigate operational default risk. This results in a positive relationship between operational spread (markup) of the firm and its bankruptcy risk, the relationship being stronger 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 hedging, exploiting recessions and the global financial crisis as correlated shocks to operational and bankruptcy risks.

Keywords: financial default, operational default, resilience, liquidity, risk management, inventory, 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 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 they 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 would 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 the tension between operation resiliency and financial efficiency, viz., the tradeoff between the firm's allocation of cash to operational hedging and to the prevention

[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

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 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 cash 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 and reduces profit margins. Firms will in general optimally choose an interior level of operational hedging in order to protect their profitability while recognizing that an operational default leads to a loss of its franchise value.

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 the 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, if the firm's operational cash flow is unrelated to its capital structure, as assumed in ours and many other models on capital structures, 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]

First, we empirically confirm that firms with greater inventory holdings and/or greater degrees of hedging along supply chains suffer less severe disruptions in output deliveries, measured by sales, when recession shocks hit. This is consistent with our model implication that operational hedging helps with firms' goods delivery in the presence of shocks to operations. Then, we establish first that the firm's markup declines in two measures of operational hedging, supply chain hedging and inventory holdings. This relationship holds after controlling for other characteristics that affect markup, such as market power and scale. A firm's markup is a reasonable summary *inverse* measure of its operational hedging intensity.

We continue to empirically test our model's central predictions on the tradeoff between operational hedging and credit risk by studying the effect of the firm's credit risk — measured by its Z-score — on its operational spread, measured by the markup. We find that higher credit risk, measured by Altman's Z-score (Altman, 2013) are positively related to the markup. This is consistent with our model's prediction. Higher financial risk necessitates the allocation of cash to financial hedging and away from operational hedging; this lowers

[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)).

output and raises the markup. The effect is economically significant: an increase of one standard deviation in the firm's negative Z-score raises the firm's markup by 6% relative to the sample median markup.

Replacing Altman's Z-score with various leverage measures, including the near-term portion of long-term debt, do not alter our results. The near-term portion of long-term debt is largely exogenous to the current state of the firm since it has been determined in the past when the debt was issued. Correspondingly, 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, compared with the effect of remaining portion of the long-term debt. Higher short-term portion of the long-term debt raises the markup about twice as strongly as does the remaining portion of long-term debt. This finding our model: the near-term pressing need to avert financial default when debt is due diverts funds from longer-term operational hedging, resulting in lower output and wider operational spread or markup. We further find that the response of the markup to credit risk (or liquidity needs) remains positive and significant even after controlling for market power, which is known to affect markup since market power enables firms to raise prices.

An important prediction of our model is that the positive markup-credit risk relationship is stronger for firms that are subject to financing constraint. By our model, the firm reduces spending on operational hedging and hoards more cash when it is harder to pledge future cash flows and use the proceeds to pay for its financial obligations, in case of a shortfall in income.

We use time series variation to test our prediction that shocks that increase the cost of financing and/or reduce credit supply should increase the positive markup-credit risk relationship. First, we use the NBER designation of recessions and find that the positive relationship between markup and credit risk is significantly stronger during recessions. At the same time, there is a more pronounced negative relationship between inventory holding and credit risk. Second, we consider shocks to firms' credit supply during the subprime crisis measured by using the measures of Chodorow-Reich (2014) who studies the negative impact on firms of a shocks to their relationship banks, such as the collapse of Lehman. As shown by the author, this shock corresponds to an exogenous increase in the affected firms' financial constraint. We find a significantly greater increase in markup for firms that were more exposed to these lending shocks and that had higher liquidity demand prior to the crisis. This test helps alleviate concerns about the endogeneity of credit risk as we study the effect of the pre-crisis liquidity demand on the post-crisis real effects for liquidity-constrained firms (Giroud and Mueller, 2016). We also find limited evidence that a reduction of inventory holdings and supply chain hedging in post-crisis era for firms with higher liquidity demand whose lenders were more adversely affected by the crisis.

We test whether market power affects the positive markup-credit risk relationship in recessions when financial constraints are tighter, as suggested by Gilchrist et al. (2017). We estimate the effect of credit risk on markup in recession separately for firms in industries whose Herfindahl index of concentration is above or below the median. The results show no difference in the markup-credit risk relationship between the two groups. Again, our results are consistent with the tradeoff between financial hedging and operational hedging and inconsistent with theories that relate this relationship to market power.

Broadly speaking, the novelty of our contribution is in studying both theoretically and empirically the determinants of operational hedging, its tradeoff with financial hedging especially for firms facing financial constraints, and its response to liquidity needs and financial shocks.[5]

## 1.1 Related literature

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

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

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).

In particular, our paper relates closely to Rampini and Viswanathan (2010). They show that more financially distressed firms may reduce risk management to save liquidity for current investment. However, our paper differs from Rampini and Viswanathan (2010) in three important ways. First, in Rampini and Viswanathan (2010), debt is fully collateralized in all states, which makes debt riskless. Thus, their model is silent regarding the relationship between a firm's credit risk and risk management. In contrast, in our model debt is risky because of risky cash flow and maturity mismatches between the firm's cash flow and debt obligations. Second, we introduce the notion of operational risk — default risk on supplier contract — that rationalizes a firm's incentive to engage in operational hedging. This notion allows us to study the relationship between credit risk and a firm's operational hedging policy. Third, one key model implication in Rampini and Viswanathan (2010) is that a firm with lower net worth does not conserve any liquidity, because its return on investment is so high that it exceeds the return on liquidity hoarding. In our paper, an incentive to conserve liquidity arises for firms with lower net worth due to the presence of risky debt. This would be reflected, in particular, in higher cash ratios for lower net worth firms, as documented in Acharya et al. (2012).

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) study 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.[6] Recently, Hu et al. (2021) theoretically show that long-term debt has the benefit of risk management — long-term creditors share the loss of the firm value during the economic downturn. Short-term creditors do not offer this risk-sharing feature. Short-term debt matures instantaneously. Consequently, short-term creditors always get full payment regardless of the firm performance, as long as the firm remains solvent. Correspondingly, we find, in Appendix I.B, that compared to the remaining portion of long-term debt, the portion of long-term debt that matures in the near future imposes a higher pressure for the firm to give up more operational hedging, in order to conserve more cash to withstand the imminent financial default risk.

Our paper adds to the emerging literature of risk management in production networks. Recently, Grigoris et al. (2022) empirically and theoretically study the relationship between credit line extension to customers and risk premia. Specifically, firms that offer more trade credit earn lower risk premia. Their explanation is as follows: by offering more trade credit to customer firms, a supplier firm hedges against its customer firms' default risk, and therefore lowers the cost of searching for new customers. Our novelty lies with the fact that we allow firms to default on both debt contracts and contracts with their customers. This give rise to the competition between financial and operational hedging for the limited liquidity resources of the firm.

Chevalier and Scharfstein (1994) suggest that liquidity-constrained firms may raise prices (or maintain higher prices in downturns) in order to boost their short-run profitability — accommodating their immediate liquidity needs — even if it hurts building a market share which is valuable in the long run. Studies of the relationship between a firm's credit risk

[6] 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 hedging as we do.

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 raise their prices and their markup while forgoing investment in increasing long-term profits. The ability to extract higher profit by raising prices is feasible for firm with market power.

We address the question of whether our results on the positive effect the price-cost spread of credit risk and constraints, which we attribute to the tradeoff between financial hedging and operational hedging, are driven by market power. Specifically, we expand our empirical tests by adding to all our models control variables that proxy for the firm's market power. In addition, we add to our model interaction terms of credit risk with market power. If the positive relation between markup and credit risk is driven by market power, the coefficients of this interaction term should be positive while credit risk on its own should have no significant effect on market. We find that the positive effect of credit risk on markup remains positive and highly significant while the interaction term of credit risk and market power is negative. Our findings are thus consistent with our theory that the positive markup-credit risk relationship can be attributed to the tradeoff between financial hedging and operational hedging rather than to the effect of 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 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 $\alpha$.[7] Figure 1 illustrates the timeline of the model.

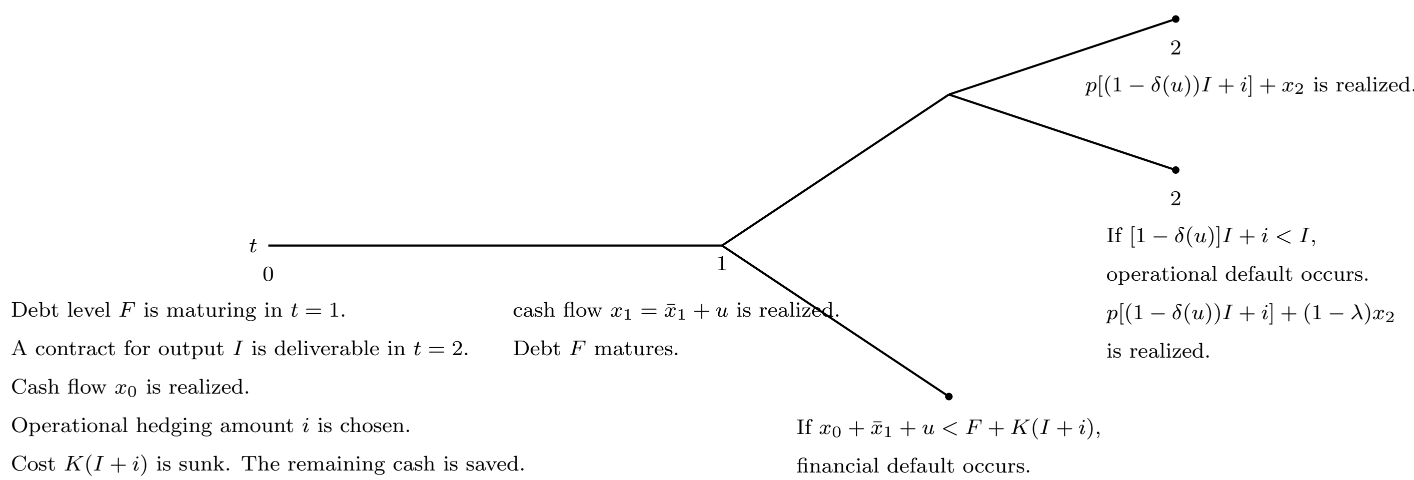


Figure 1: The timeline of the model

[7]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).

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.[8] The cost of the production and operational hedging is 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, $c + x_1$. 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.

[8]In our model the firm is operationally inflexible in the sense that its production amount is confined by the size of the customer contract. We do so to focus on the firm's operational hedging decisions, rather than its investment/disinvestment decisions.

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 the debt contract and the supplier contract. Third, external financing cannot be raised against the income from the supplier contract settlement at date-2. If the firm can pledge a large enough fraction of the income from the supplier contract settlement as collateral, then current and future cash holdings can be viewed as 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 $\tau$ of its cash flow from contract settlement at $t = 2$, and shows that our main results hold as long as $\tau$ is sufficiently small, i.e., the pledgeability level is sufficiently low. Fourth, the shock at $t = 1$ must affect both the date-1 cash flow and the firm's ability to honor the supplier contract. Although we assume a single random shock that affects both the cash flows from assets in place and its production capacity, extending our model to multiple shocks is possible.

## 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 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 level ($i$). 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 $\delta$ is decreasing in $u$, its inverse function $\delta^{-1}$ is decreasing in $i$. This means that the operational default boundary $u_O$ is decreasing with $i$, the level 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 $\lambda$ 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:

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

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

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

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.1, we show that $\bar{i}$ is also the unique optimal hedging level that maximizes the equity value (2.5), under some mild technical conditions.

The following assumption ensures that the firm has enough cash flow at date-0 to choose the highest optimal operational hedging level $\bar{i}$, when $\bar{F}$ is sufficiently small such that $u_F = 0$:

**Assumption 2.1.**

$$K(I+\bar{i}) < x_0 \ , \quad (2.7)$$

*where $\bar{i}$ is the solution of equation* (2.6).

Since $D(i, \bar{F})$ is continuous in $\bar{F}$, $u_F$ is always smaller than $u_O$ for $i \in [0, \bar{i}]$ when $\bar{F}$ is sufficiently small.

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 under extremely high and low net debt levels $\bar{F}$ under which the relative magnitudes of $u_F$ and $u_O$ does not change with $i \in [0, \bar{i}]$; then we characterize the relationship between the hedging policy and the net debt level.[9]

## 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 for $i \in [0, \bar{i}]$, 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 the firm's period-2 cash flow and franchise value, conditional on the firm not defaulting in the interim.

Equity holders choose the level of operational hedging $i$ to maximize equity value $E$ in (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 cash flow and franchise value at

[9] 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.

the financial default boundary. Define $i^*$ as the firm's hedging policy that satisfies (2.9). On the one hand, a marginal increase in operational hedging yields 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 cash flow and 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 hedging policy $i^*$ such that the markup is equal to the marginal increase of the expected financial default cost.

Comparing the first-order conditions (2.6) and (2.9), it is straightforward that $\bar{i} > i^*$.[10] We show in Appendix IA.2 that the first-order condition (2.9) admits a unique and positive interior solution $i^*$ that maximizes $E$ subject to $D(i, \bar{F}) > 0$ for $i \in [0, \bar{i}]$.[11]

Lemma 2.1, proved in Appendix IA.2, states that the optimal optimal operational hedging policy decreases in the firm's net debt level $\bar{F}$ in this case:

**Lemma 2.1.** *When $\bar{F}$ is sufficiently high such that $u_F > u_O$ for $i \in [0, \bar{i}]$, the optimal operational hedging policy $i^*$, if exists, 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 for $i \in [0, \bar{i}]$. 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 the date-2 franchise value, $\lambda x_2$. The equity value is:

$$\hat{E} = E - \int_{u_F}^{u_O} \lambda x_2 g(u) du \ , \tag{2.10}$$

[10]We prove this claim formally in Appendix IA.3.

[11]A technical assumption must also be satisfied. Please refer to Appendix IA.2 for details.

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

$$p - K'(I+i) = [V(u_F, i) - \lambda x_2]h(u_F)K'(I+i) + \frac{\lambda x_2 g(u_O)}{[1 - G(u_F)]I\delta'(u_O)} \ . \tag{2.11}$$

Define $\hat{i}^*$ as the firm's hedging policy that satisfies (2.11). 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 increases the expected cost of financial default by increasing the financial default boundary $u_F$.[12] On the other hand, a marginal increase in operational hedging decreases the expected cost of operational default since it reduces the operational default boundary $u_O$, which is captured by the last term of the first-order condition (2.11). Therefore, the first-order condition (2.11) says that the firm chooses the 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.3 that the first-order condition (2.11) admits a unique and positive interior solution $\hat{i}^*$ that maximizes $E$ subject to $D(i, \bar{F}) > 0$ for $i \in [0, \bar{i}]$, under some mild technical conditions.

Comparing the first-order conditions (2.6), (2.9) and (2.11), it is straightforward that $\bar{i} > \hat{i}^* > i^*$. Intuitively, when the firm's inherited net debt $\bar{F}$ is sufficiently low such that the operational default boundary $u_O$ dominates the financial default boundary $u_F$, and in turn, operational default risk is the main concern of equity holders, in this case, the firm will invest more on operational hedging. The following lemma, proved in Appendix IA.3, formalizes the above statement.

**Lemma 2.2.** *If the production commitment $I$ is sufficiently high and $\frac{K'(I+\bar{i})}{I}$ is sufficiently low, then $\bar{i} > \hat{i}^* > i^*$.*

[12]Notice that the loss conditional on a financial default is reduced by $\lambda x_2$. This is because the firm has already lost $\lambda x_2$ due to operational default when it declares financial default.

Similar to the $u_F > u_O$ case, in Appendix IA.3, we prove that when $u_F < u_O$ for $i \in [0, \bar{i}]$, the firm's optimal operational hedging policy $\hat{i}^*$ decreases in its inherited net debt level:

**Lemma 2.3.** *When $\bar{F}$ is such that $0 < u_F < u_O$ for $i \in [0, \bar{i}]$, the optimal operational hedging policy $\hat{i}^*$, if exists, decreases in the firm's net debt level $\bar{F}$.*

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

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 hedge against the financial default risk. As a result, the optimal operational hedging, denoted by $i^{**}$, is lower.

**Proposition 2.1.** *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. The model can be extended 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. The results from such extension are qualitatively identical to the base case in which the firm cannot pledge any date-2 cash flow to the creditors.

Suppose that at $t = 1$ the firm can use a fraction $\tau$ 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, $\tau$ 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 $u_{F,PP}$, $\tau p[(1-\delta(u_{F,PP}))I+i$.[13] 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:

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

As long as $\tau$ 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.

**Proposition 3.1.** *If $\tau < \bar{\tau}$, 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 in Section 2. Since all the quantities are continuous in $\tau$, Proposition IA.2 and Proposition 3.1 hold for small enough $\tau$, 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 $L$ minus 1. The market value of debt is given as:

$$L = F - \int_0^{u_F} \left[u_F - u - \tau p\left(\delta(u_F) - \delta(u)\right) I\right] g(u)du \ . \tag{3.2}$$

[13]Raising this amount is always feasible for $u \in [u_{F,PP}, \infty]$. Recall that $\delta u$ decreases in $u$ by assumption, thus the pledgeable income $\tau p[(1-\delta(u))I+i]$ increases in $u$.

The second term of Equation (3.2) is the expected bankruptcy cost. Then, the credit spread $s$ is

$$s = \frac{F}{L} - 1 \; . \tag{3.3}$$

The operational spread is the markup, $p - K'(I+i)$. In the next section, we numerically show that the operational spread and credit spread are positively correlated. Intuitively, holding $x_0$ and $\bar{x}_1$ constant, the optimal operational hedging policy $i^{**}$ decreases in debt level $F$ by Proposition 2.1. Thus, credit spread and operational spread are positively correlated, as long as the market price of debt, $\frac{L}{F}$, decreases in $F$.

## 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 $\tau$ 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 degree of the mismatch between the firm's debt maturity structure and the duration of its operational cash flows.

## 3.4 Hedging along the supply chain

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.[14] 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 $\frac{\partial u_O}{\partial n} = -\frac{\delta_n(u_O,n)}{\delta_u(u_O,n)} < 0$. 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 hedging ($n$) is decreasing in the 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.[15]

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

[14] 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.

[15] 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.

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: 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 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 $\tau$. 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 $\tau$.[16]

[INSERT Figure 1.]

In what follows, we plot the firm's credit spread against its operational spread, i.e., the markup $p - K'(I + i)$. Along the equilibrium path of the optimal hedging policies given different debt levels $F$, the credit spread and operational spread are positively correlated. This positive relationship is stronger when the firm's pledgeability $\tau$ 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, leading to a higher markup.

[INSERT Figure 2.]

[16]From Equation (IA.32), $\bar{F}_{fb}$ increases in the pledgeability $\tau$. Thus the $F$-region in which debt level does not affect the optimal hedging policy increases with $\tau$.

# 5. Empirical analysis

Before we present our empirical results, the following example demonstrates the intertwining of a firm's credit risk and its operational hedging policies. Vail Resorts, Inc., a mountain resort company which is included in our sample, was heavily indebted before the subprime mortgage crisis and the great recession. In its 2008 and 2009 annual reports, management expressed concerns regarding the company's highly levered capital structure. Item 1A, Risk Factors, says: "Our indebtedness could adversely affect our financial health and prevent us from fulfilling our obligations." To make things worse, its lenders (e.g., U.S. Bank and Wells Fargo) experienced a 2.7% drop in loan provision during the financial crisis. Correspondingly, Vail held 5.6% less inventory (on average, scaled by its sales) during the recession years compared to the periods before that. As shown in FactSet Revere database, it also terminated the strategic alliance program with Ricoh Co., Ltd. a Japanese company that was Vail's office equipment supplier and stopped being a significant customer with General Mills, a consumer food company. In the meantime, its markup increased by 10.7%.

## 5.1 An overview of empirical tests

Before delving into the model-implied relationship between credit risk and operational spread, we first empirically validate that our proposed measures of operational hedging are consistent with our model mechanics. Recall that in the model, the operational hedging compensates the shocks to firm's production, which equivalent to its sales, given that the firm is a price-taker in the model. Accordingly, we empirically validate our proposed measures for operational hedging, namely, inventory holding and supply chain hedging, defined below in Section 5.2, do mitigate the negative shocks to firm sales, as the model suggests. Since the shocks in our model is systematic in nature, we use NBER-designated recessions as indicators to these negative shocks. The model also assumes a one-to-one relationship between operational hedging and the unit production cost, thus, the operational spread. We document that the markup, our measure of operational spread, is negatively correlated with indicators associated with operational hedging. 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 hedging. 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.

Next we move to the central predictions of the model. Our model shows that operational hedging declines with the required liquidity to cover imminent debt obligations induces the firm to allocate more resources to avert financial default and spend less on operational hedging, which results in lower costs and higher price-unit cost margin or operational spread. In the model, this liquidity requirement manifests itself in terms of a higher credit risk, as illustrated by the positive relationship between credit spread and operational spread in Figure 2. It is also related to existing leverage, especially the portion that is due soon, holding the pledgeable income level constant. Moreover, the relationship between liquidity requirement and operational spread is more pronounced when the firm's income pledgeability is lower.

We test these implications as follows. We empirically document a positive relationship between negative Z-score and markup, as predicted by our model. In Appendix I.B, we also find that such positive relationship holds when we replace negative Z-score with leverage, especially maturing long-term leverage, measured as the long-term debt that matures within two years. We further show that the positive relation between operational spread and liquidity requirement is stronger when the firm faces pledgeability constraints. Moreover, we find that the markup-credit risk relationship remains positive and highly significant regardless of the firms' market power, which some theories suggest to affect it.

In addition, we use two time-series variations in pledgeability constraints 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 credit risk is stronger during recession periods, designated by NBER. This is consistent with our theory that the tradeoff between financial risk and operational risk, made more critical in recessions, drives a positive relation between markup and credit risk. We further test and find no support for theories suggesting that market power is what drives the positive markup-credit risk relationship in general or in periods of recessions. Moreover, we find that inventory drops more drastically during the recession for firms entering the 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 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 debt policies and credit risk; studies of the impact of the financial crisis show that pre-crisis financial strength 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 spread 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. 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)[17]. We use the negative value of Z-score so that a higher value means that the firm has greater financial risk. In Appendix I.B, we also use financial leverage, the financial debt ($DLTTQ+DLCQ$) divided by total assets ($ATQ$), and 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, as alternative measures of firms' liquidity needs to fulfill imminent debt obligations.[18] 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 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

[17] 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.

[18] In Compustat, $DD1$ is included in $DLCQ$.

operational hedging, supply chain hedging. Indeed our model accommodates supply chain hedging 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.[19] 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 hedging 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 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 hedging using the three aforementioned individual measures.

(1) Supply chain hedging index, the first principal component score from a principal component analysis using three individual measures: supply chain hedging index = $0.5745\times$ln(1+number of suppliers)$+0.5796\times$ln(1+number of supplier regions)$+0.5779\times$ ln(1+number of out-of-region suppliers).[20] A higher supply chain hedging index indicates a more intensified hedging along the supply chain.

(2) Supply chain hedging ranking is defined as follows: First, we calculate the negative value of the average firm-quarter ranking for each of the individual supply chain hedging variable, across the three supply chain hedging variables. Supply chain hedging ranking is then defined as the average ranking scaled by the number of non-missing values of

[19] 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).

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

the average ranking. A larger value of supply chain hedging ranking indicates a more intensified hedging along the supply chain.

Finally, our analysis also includes inventory ($INVTQ$) divided by sales as another 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.]

### 5.3 Hedging the operational risk through supply chain and inventory

As shown in Section Section 2, operational hedging in our model — indicated by $i$ — can be interpreted as either building up extra inventory or a more stable supply chain. Greater $i$ increases production expenditures, but importantly, enables to deliver higher sales in times of severe economic shocks — indicated by lower $u$. We now examine the effect of our measures of operational hedging — inventory holding and supply chain hedging — on firm sales during recession periods (as designated by the NBER).

For each recession period, we estimate a cross-sectional regression for each recession separately with the dependent variable being $\Delta sales/assets$, the change in the average level of firm sales (scaled by total assets) between the recession periods and the eight-quarter period before the recessions. Because recessions often have warning signs which may affect the firm's operational hedging before the onset of the recession, we use the inventory-sales ratio and the supply chain hedging (supply chain hedging index or supply chain hedging rank) from four quarters before the onset of each recession.[21] The control variables include Tobin's $Q$, the natural logarithm of total assets, cash holdings, cash flow, asset tangibility, a dummy variable for the top-3 sellers in their respective industry, and firm's sales/industry sales. All the control variables are fixed as of the latest quarter before the onset of the

[21] Using average operational measures across five to eight quarters before the onset of recessions yields similar results.

recession. The model includes Fama-French's 38 industry fixed effects and we cluster the standard errors at industry level.

Table 3 presents the results. Sales naturally declined during the recessions.[22] Importantly, a higher level of inventory before the recession mitigates the decline in sales during the recession compared with the average sales during the eight pre-recession quarters. This holds for all six recessions. For three of them, the positive effect of inventory is significant at the 0.05 level, for two the effect is significant at the 0.10 level and for one recession (1981Q2 to 1982Q2) it is positive and insignificant. For the supply chain hedging variables, we have data only for the recession of 2007Q4 to 2009Q2. In Panel B we find that a higher level of pre-recession supply chain hedging mitigates the decline in sales during the recession. The positive effect of supply chain hedging on sales is significant for both our measures of such hedging. Overall, our results show that firms with more intensive operational hedging suffer less severe disruptions in output deliveries, measured by sales, when recession shocks hit.

[INSERT Table 3.]

It is expected that sales decline during recessions because demand falls. But a decline in demand should affect firms' sales independently of their inventory, which is part of supply. Our finding that the shock to sales due to a recession is mitigated for firms with operational hedging — firms with higher inventory and a greater extent of supply chain hedging — is consistent with our model setup by which the shock $u$ hits both period-1 cash flows and period-2 production capacity, that is, it raises $\delta(u)$ and thus reduces the firm's production capacity $(1-\delta(u))I$, which is independent of the level of operational hedging $i$ that is set in period 0.

[22]The average sales-assets ratio is 0.011 lower during the recessions, compared with the previous eight-quarter periods. The average decline in sales-assets ratio ranges from $-0.019$ to 0.007, across the six recessions in our sample. Apart from the first recession (1973Q4 — 1975Q1), all recessions witness an average decline in sales-assets ratio.

## 5.4 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 $t$,

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

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 hedging 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 Fama-French 38 Industry × year-quarter fixed effects with standard errors clustered by firm and by year-quarter.

[INSERT Table 4.]

By the results in Table 4, 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. The two measures of supply chain hedging indicate that markup is declining in the PCA index of the three supply chain hedging variables; and it is decreasing in the negative value of the average ranking of the three variables. 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 hedging, which means a decline by one unit, increases *Markup* by 0.03 which is 9% of its mean. By the estimation in column (1), one standard deviation increase in Supply chain hedging index will lower markup by 0.008, 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.[23]

## 5.5 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 Fama-French 38 Industry $\times$ year-quarter fixed effects.

[INSERT Table 5.]

Table 5, Panel A, presents our baseline results. As predicted in Proposition 3.1 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 6% of the sample median markup. In Table IB.2, we also find a statistically significant and negative relationship between leverage, especially the long-term leverage maturing in the next two years, and markup. Together, the empirical results are consistent with model predictions. In

[23] Using individual supply chain hedging measures instead of composite measures yields qualitatively similar results.

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.[24]

Figure 3 presents binned scatter plots of the relationship between operational spread and -(Z-score). Following the methodology of Rampini et al. (2014),[25] we first residualize *Markup* and -(Z-score) with respect to the baseline control variables (including the firm and year-quarter fixed effects), as in Table 5.[26] We then add back the unconditional 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. Section 6 correspond to the estimations of Table 5. We see that the markup monotonically increases with one-period lagged values of -(Z-score). 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.

[INSERT Section 6.]

## 5.6 The effect of market power

In our model, the firm's credit risk induces a rise in markup because a higher such risk induces the firm to hoard resources to avert financial default and lower expenses on operational hedging, which in turn lowers the unit cost and raises markup for any given price. Chevalier and Scharfstein (1994) and Gilchrist et al. (2017) propose that firms subject to liquidity constraint may raise price in order to increase their short-term cash flow while forgoing the

[24]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.

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

[26]Inclusion of industry × year-quarter fix effects renders too many variables for the Stata program Binscatter to handle.

benefit of increasing their market share in the long run. The benefit is greater for firms with market power whose customer base is sticky. We therefore expect a more positive effect of credit risk on markup for firms with market power.

We test the role of market power on the markup-credit risk relationship by adding to the model estimated in Table 5 an interaction term, -(Z-score) $\times$ $\text{MP}_k$, where $\text{MP}_k$ is one of the three measures of market power that are already included in the model as control variables. $\text{MP}_k$ is (1) a dummy variable for the top 3 industry seller (and zero otherwise); (2) Sales/total industry sales; or (3) Herfindahl index of the industry, using Fama and French's 38 industries classification. If firms with greater market power raise prices in response to greater credit risk and liquidity needs as predicted by the aforementioned theories, the coefficient of -(Z-score) $\times$ $\text{MP}_k$ should be positive while -(Z-score) on its own should be insignificant.

The results in Table IC.1 are consistent with our model while being inconsistent with the prediction that the rise in markup is associated with market power. We find that the coefficients of -(Z-score) $\times$ $\text{MP}_k$ for $k = 1, 2, 3$ are, respectively, $-0.003$ ($t = -2.35$), $-0.071$ ($t = -3.81$) and $-0.009$ ($t = -2.34$). The coefficient here is statistically negative rather than positive as predicted by the market-power theories. Importantly, the coefficients of -(Z-score) remain positive and highly significant, consistent with our theory on the tradeoff between financial hedging and operational hedging. The respective being respectively 0.003 ($t = 6.18$), 0.003 ($t = 6.23$) and 0.004 ($t = 6.01$).

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. To conserve space, we did not include the tabulated results of this subsection in the paper. The tabulated results regarding the effect of market power on the interaction between credit risk and markup are available upon request.

## 5.7 Recessions periods

During recession periods, firms' liquidity needs can be higher, either due to lower pledgeability of their future cash flows (lower $\tau$), or due to higher level of net indebtedness ($\bar{F}$).[27] Consequently, the tension between financial hedging and operational hedging is intensified during recessions.

In this section, we augment the baseline estimation in Table 5 with interaction terms between firms' liquidity position indicators and a dummy variable for recession periods according to NBER. 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 6 presents the results. Panel A shows that firms entering recession periods with higher -(Z-score) have a greater increases in markup, indicated by the positive and significant coefficients of the interaction terms -(Z-score) $\times$ Recession, where Recession equals one during the quarters designated as recessions by the NBER (and zero otherwise). Panel B shows that firms with more precarious liquidity positions at the onset of recessions, measured by -(Z-score), decrease inventory-sales ratio, indicated by the negative and statistically significant coefficients on the interaction terms between -(Z-score) and Recession.[28] Panel C and D examine the two measures of supply chain hedging. We do not find any statistically significant relationship between firms' supply chain adjustment during the recessions and their pre-recession liquidity positions.[29]

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

[28] 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.

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

[INSERT Table 6.]

We attend again to the theory from Gilchrist et al. (2017) that increased credit risk during economic downturns induces firms with market positive to raise prices and markups. We augment the model of table 6 with interaction terms among market power variables, liquidity demand variables and the dummy variable for recession, as well as the interaction terms between market power variables and liquidity demand variables, and interaction terms between market power variables and the dummy variable for recession. The triple interaction terms among market power variables, -(Z-score) and the dummy variable for recession are insignificant, as indicated by Table IC.2.[30] We conclude that there is no evidence that market power is what drives the positive markup-credit risk relationship in general or in recession periods.

## 5.8 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. 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

whereas quarter fixed effects do not increase the R-squared noticeably.

[30]The coefficients on the interaction terms among market power variables, leverage/Maturing LT leverage, and the dummy variable for recession are significantly negative.

to measure the negative impact of the subprime mortgage crisis on lenders' abilities to extend credit to the borrowers.[31] 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 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.

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

where $j, k, t$ stands for a firm $j$ in industry $k$ in quarter $t$.

We estimate the differential effect on $Markup_{j,t}$ for firms that entered the post-crisis period with different levels $X_{j,2007}$ being -(Z-score), given different levels of the firm's exposure

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

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 5) 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 $\beta_1$, the coefficient of the interaction between the crisis exposure and the credit risk variables. The model includes firm and Fama-French 38 Industry $\times$ year-quarter fixed effects and standard errors are at firm levels.[32] 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 $\beta_1$ is positive and significant for all interactive terms except for the $-$(z-score) $\times$ Lehman exposure. Our results indicate 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. Using two alternative exposures to financial crisis yields qualitatively similar results. In Table IB.4, we also find that firms with higher total pre-crisis leverage witness a larger increase in markup if their lenders are more exposed to the subprime mortgage crisis. Again, Table IC.3 shows that market power does not play a role in the relationship between a firm's change in markup and its interaction term between -(Z-score) and the extent to which its lenders are exposed to the financial crisis, as indicated

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

by the insignificant triple interaction terms among market power variables, -(Z-score) and lender exposure variables.

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, 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 in Panel B. 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 higher -(Z-score), refocus their supply chains in post-crisis period, if their lenders are 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) of Panel C and D. However, the above results are not robust if we measure lenders' exposure to financial crisis using the other two measures: proportional changes in loan supply by firms' lenders during the crisis and connections to Lehman Brothers.

In Table IB.4, we examine the impact of the interaction between firms' lender exposures to financial crisis and other measures of their liquidity needs — total leverage and maturing long-term leverage — on their markups and individual measures of operational hedging. We find that firms with higher overall leverage before the crisis witness larger drops in inventory-sales ratios, 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 odd-numbered columns of Panel B. Moreover, firms entering the crisis with higher total 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 Leverage and Lender exposure, in columns (3) and (5) of Panel C and D. Overall, we find limited evidence that firms adjusted their inventory and supply chain hedging in response to severe liquidity shortage in the way that our model suggests. 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.

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 — -(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) — 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 markups. 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. Figure 4 illustrates the point estimates, as well as the 95% confidence intervals of the coefficients on the product of -(Z-score) and alternative measures of lender exposure for the periods of four quarters before and after the financial crisis. Lastly, the results are qualitatively similar when replacing -(Z-score) with Leverage or Maturing LT Leverage, as indicated by Table IB.5 and Table IB.6, respectively.

[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 study the corporate choice between financial efficiency and operational resiliency. We build 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 present empirical evidence supporting our model predictions. First, we document that markup is a reasonable summary of firms' operational hedging activities, measured as inventory holdings and supply chain diversification. Then we document a positive relationship between the markup and 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 during recessions and in the aftermath of the subprime financial crisis for firms whose 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.

We conclude by pointing out fruitful areas for future research. 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.

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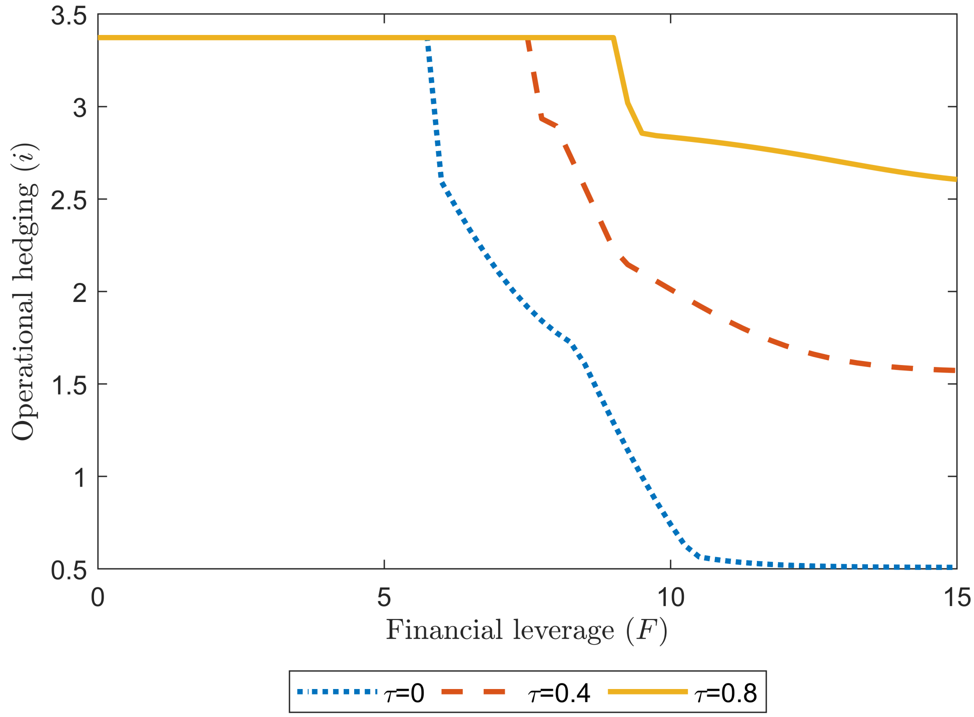


Figure 1: **Firm's optimal hedging policy $i^{**}$ and debt level $F$**

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.

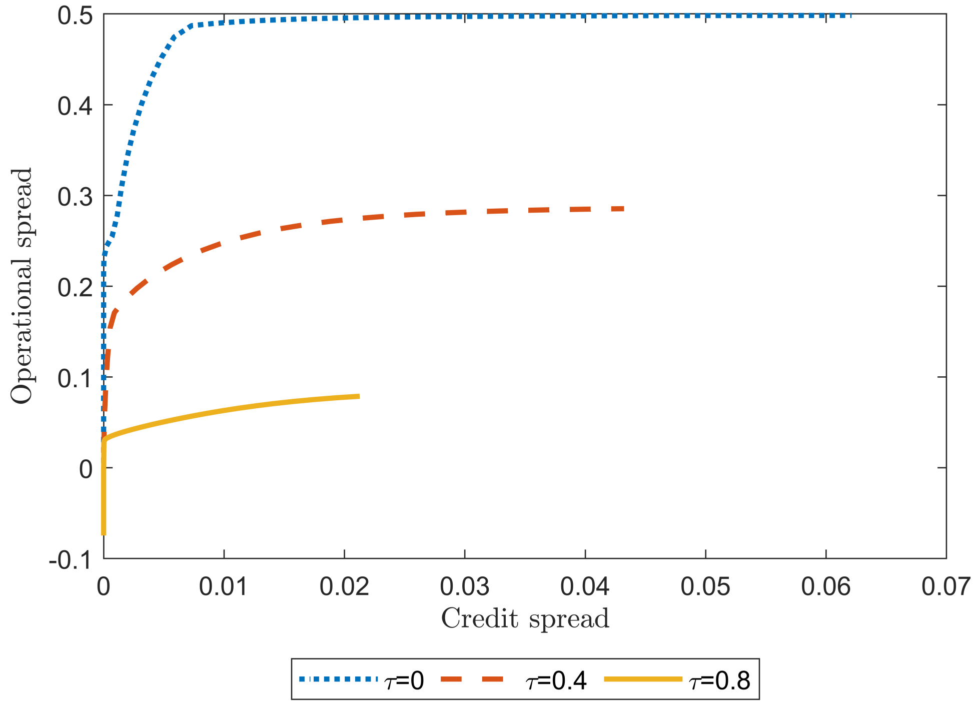


Figure 2: **Credit spread and operational spread**

The credit spread and operational spread under the optimal hedging policy $i^{**}$ given debt level $F$ for $\tau = 0$, $\tau = 0.4$ and $\tau = 0.8$, where $\tau$ is a measure of the extent of the need for pledgeability, which proxies financial constraint. All other parameters are presented in Table 1.

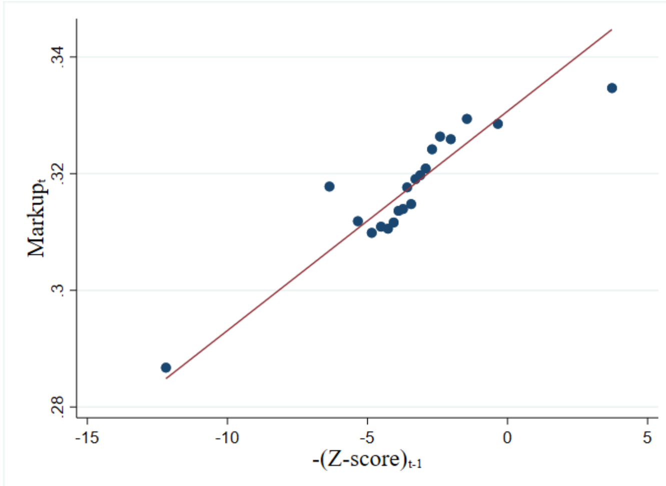


Figure 3: **Markup and -(Z-score)**

We first residualize the y-axis variable and x-axis variable with respect to the baseline control vector (including the firm and year-quarter fixed effects) in Table 5. 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 |
|---|---|---|
| $\alpha$ | Rate of the exponential distribution of $u$ | 0.05 |
| $I$ | Contractual delivery amount | 3 |
| $\kappa$ | Production cost parameter | 0.1 |
| $\lambda$ | 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. 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 hedging index, and Supply chain hedging 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 hedging index is the first principal component score from a principal component analysis (PCA) that equals $0.5745 \times \text{(i)} + 0.5796 \times \text{(ii)} + 0.5779 \times \text{(iii)}$ where (i)-(iii) indicate the above three measures. Supply chain hedging 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 hedging 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 |
| 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 hedging index | 116,320 | -0.009 | 1.697 | -1.334 | -0.381 | 0.964 |
| Supply chain hedging ranking | 116,320 | -0.500 | 0.268 | -0.730 | -0.515 | -0.274 |

## Table 3: **The effect of operational hedging on changes in sales during NBER recessions**

Cross-sectional regressions of changes in the sales/assets ratio during recessions on the pre-recession level of firms' operational hedging. The dependent variable is Δ sales/assets, the difference between its average level of the recession quarters and its average over eight quarters before the recession. The recession quarters are so designated by the NBER. The main independent variables are the inventory/sales ratio or supply chain hedging measured by the supply chain hedging PCA index or its ranking, fixed at four quarters before the onset of recession (or earlier). The control variables include Tobin's $Q$, natural logarithm of total assets, cash holdings, cash flow, asset tangibility, a dummy variable for the top-3 sellers in their respective industry, and firm's sales/industry sales. All the control variables are fixed as of the latest quarter before the onset of each recession. We include Fama-French 38 industry fixed effects and cluster the standard errors at industry level. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively.

| VARIABLES | Δ *sales/assets* | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: Using Inventory-sales ratio | | | | | | |
| Recession period | 1973Q4 — 1975Q1 | 1979Q2 — 1980Q2 | 1981Q2 — 1982Q2 | 1989Q4 — 1991Q1 | 2001Q1 — 2001Q3 | 2007Q4 — 2009Q2 |
| Inventory/sales | 0.021* | 0.015** | 0.010 | 0.014*** | 0.018*** | 0.009* |
| T-stat | 1.98 | 2.61 | 1.53 | 3.31 | 3.97 | 1.79 |

Panel B: Using two Supply chain hedging variables, for the recession of 2007Q4 to 2009Q2

| | SCH PCA index | SCH ranking |
|---|---|---|
| Supply chain hedging (SCH) | 0.002*** | 0.012** |
| T-stat | 3.09 | 2.10 |
| Control variables | Yes | |
| FF-38 industry fixed effects | Yes | |

## Table 4: **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 and Sales/total sales. All explanatory variables are lagged by one quarter. The regressions include firm and Fama-French 38 Industry × 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 hedging index | -0.0048** | |
| | (0.0024) | |
| Supply chain hedging ranking | | -0.031** |
| | | (0.013) |
| Inventory/sales | -0.047*** | -0.047*** |
| | (0.015) | (0.015) |
| Control variables | Yes | |
| Firm fixed effects | Yes | |
| Industry × year-quarter fixed effects | Yes | |
| Observations | 115,995 | 115,995 |
| R-squared | 0.754 | 0.754 |

Table 5: **Markup and credit risk**

Estimation of the relationship between Markup and -(Z-score). The dependent variable in the panel regression is the quarterly Markup. 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, and Sales/total sales. All explanatory variables are lagged by one quarter. The regressions include firm and Fama-French 38 Industry $\times$ 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) |
| -(Z-score) | 0.0033*** |
| | (0.00054) |
| Tobin's Q | 0.020*** |
| | (0.0019) |
| Ln(total assets) | 0.0097*** |
| | (0.0028) |
| Cash holdings | -0.064*** |
| | (0.015) |
| Cash flow | 0.85*** |
| | (0.037) |
| Asset tangibility | -0.0076 |
| | (0.014) |
| Top 3 industry seller | 0.0060 |
| | (0.0055) |
| Sales/industry sales | -0.643*** |
| | (0.124) |
| Firm fixed effects | Yes |
| Industry $\times$ year-quarter fixed effects | Yes |
| Observations | 571,135 |
| R-squared | 0.630 |

Table 6: **Operational hedging and credit risk: NBER recessions**

Regressions of Markup, Inventory and Supply chain hedging on firms' -(Z-score) that interacts with Dummy variable for NBER recession periods. We exclude the Covid-related recession during the first two quarters of 2020. *Recession* = 1 if the quarter is classified as NBER recession, and = 0 otherwise. For each recession, the values of -(Z-score) 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 5. Panel A examines markup. Panel B examines inventory- sales ratio. Panels C and D examine the two measures of supply chain hedging (SCH) variables — Supply chain hedging index (SCH index) and Supply chain hedging ranking (SCH ranking), respectively. The variable definitions are in Table 2. The regressions include firm and Fama-French 38 Industry × 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: *SCH index* | Panel D: *SCH ranking* |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| -(Z-score) × Recession | 0.002*** | -0.002*** | -0.001 | -0.000 |
| | (0.001) | (0.001) | (0.002) | (0.000) |
| -(Z-score) | 0.003*** | -0.003*** | 0.011*** | 0.002*** |
| | (0.001) | (0.000) | (0.002) | (0.000) |
| Control variables | | Yes | | |
| Firm fixed effects | | Yes | | |
| Industry × Year-quarter fixed effects | | Yes | | |
| Observations | 560,911 | 549,872 | 113,343 | 113,343 |
| R-squared | 0.632 | 0.725 | 0.861 | 0.814 |

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

Regressions of Markup, Inventory- sales ratio and supply chain hedging on firms' -(Z-score) that interacts 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) are as of the end of 2007. The firm-level control variables, as in Table 5, 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 hedging (SCH) — Supply chain hedging index (SCH index) and Supply chain hedging ranking (SCH ranking), respectively. The variable definitions are in Table 2. The regressions include firm and Fama-French 38 Industry × year-quarter 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

| VARIABLES | Dependent variable: *Markup* | | |
|---|---|---|---|
| | % # Loans reduction | Lehman exposure | ABX exposure |
| | (1) | (2) | (3) |
| -(Z-score) × Lender exposure | 0.086** | 0.164** | 0.085*** |
| | (0.034) | (0.069) | (0.027) |
| Lender exposure | -0.742* | -1.034 | -0.876** |
| | (0.446) | (0.688) | (0.401) |
| Control variables | | Yes | |
| Control variables × Lender exposure | | Yes | |
| Firm fixed effects | | Yes | |
| Industry × year-quarter fixed effects | | Yes | |
| Observations | 20,926 | 20,926 | 20,926 |
| R-squared | 0.905 | 0.905 | 0.905 |

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

| VARIABLES | Dependent variable: *Inventory/sales* | | |
|---|---|---|---|
| | % # Loans reduction | Lehman exposure | ABX exposure |
| | (1) | (2) | (3) |
| -(Z-score) × Lender exposure | -0.104 | -0.219 | -0.084 |
| | (0.073) | (0.152) | (0.058) |
| Lender exposure | 0.833 | -0.662 | 0.707 |
| | (1.027) | (2.124) | (0.978) |
| Control variables | | Yes | |
| Control variables × Lender exposure | | Yes | |
| Firm fixed effects | | Yes | |
| Industry × year-quarter fixed effects | | Yes | |
| Observations | 20,532 | 20,532 | 20,532 |
| R-squared | 0.883 | 0.883 | 0.883 |

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

| VARIABLES | Dependent variable: *Supply chain hedging index* | | |
|---|---|---|---|
| | % # Loans reduction | Lehman exposure | ABX exposure |
| | (1) | (2) | (3) |
| -(Z-score) × Lender exposure | -0.300 | -1.129 | -0.502* |
| | (0.312) | (0.726) | (0.261) |
| Lender exposure | 0.647 | 17.316* | 11.780** |
| | (5.666) | (9.869) | (4.638) |
| Control variables | | Yes | |
| Control variables × Lender exposure | | Yes | |
| Firm fixed effects | | Yes | |
| Industry × year-quarter fixed effects | | Yes | |
| Observations | 13,860 | 13,860 | 13,860 |
| R-squared | 0.938 | 0.938 | 0.938 |

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

| VARIABLES | Dependent variable: *Supply chain hedging ranking* | | |
|---|---|---|---|
| | % # Loans reduction | Lehman exposure | ABX exposure |
| | (1) | (2) | (3) |
| -(Z-score) × Lender exposure | -0.046 | -0.183 | -0.087* |
| | (0.061) | (0.139) | (0.051) |
| Lender exposure | -0.030 | 2.822 | 1.976** |
| | (1.091) | (1.857) | (0.932) |
| Control variables | | Yes | |
| Control variables × Lender exposure | | Yes | |
| Firm fixed effects | | Yes | |
| Industry × year-quarter fixed effects | | Yes | |
| Observations | 13,860 | 13,860 | 13,860 |
| R-squared | 0.913 | 0.913 | 0.913 |

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

Regressions of Markup on firms' -(Z-score) that interacts with the extent of lender exposures to the 2008 financial crisis in each quarter $D_n$, $n = -1, -2, -3, -4, +1, +2, +3, +4, +5 + (+5 — +8)$ 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) are as of the end of 2007. The firm-level control variables, as in Table 5, 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 $-(Z - score)$ and the size of $LE$ for quarters $D_n$. The regressions include firm and Fama-French 38 Industry × year-quarter fixed effects. Standard errors are clustered by firm. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively.

| VARIABLES | Dependent variable: *Markup* | | |
|---|---|---|---|
| | % # Loans reduction | Lehman exposure | ABX exposure |
| $-(Z - score) \times LE$, $D_{-4}$ | 0.015 | 0.069 | 0.014 |
| | (0.024) | (0.047) | (0.019) |
| $-(Z - score) \times LE$, $D_{-3}$ | -0.018 | -0.015 | -0.009 |
| | (0.025) | (0.060) | (0.020) |
| $-(Z - score) \times LE$, $D_{-2}$ | 0.008 | 0.050 | 0.022 |
| | (0.025) | (0.048) | (0.020) |
| $-(Z - score) \times LE$, $D_{-1}$ | 0.020 | 0.078 | 0.027 |
| | (0.027) | (0.051) | (0.021) |
| $-(Z - score) \times LE$, $D_1$ | 0.058 | 0.133 | 0.063* |
| | (0.045) | (0.089) | (0.037) |
| $-(Z - score) \times LE$, $D_2$ | 0.124*** | 0.246*** | 0.118*** |
| | (0.041) | (0.079) | (0.032) |
| $-(Z - score) \times LE$, $D_3$ | 0.134*** | 0.267*** | 0.126*** |
| | (0.040) | (0.078) | (0.031) |
| $-(Z - score) \times LE$, $D_4$ | 0.079* | 0.170** | 0.088*** |
| | (0.041) | (0.080) | (0.032) |
| $-(Z - score) \times LE$, $D_{+5+}$ | 0.079* | 0.167** | 0.084** |
| | (0.041) | (0.085) | (0.033) |
| Lender exposure, $D_n$ | | Yes | |
| Control variables | | Yes | |
| Control variables × Lender exposure | | Yes | |
| Firm fixed effects | | Yes | |
| Industry × year-quarter fixed effects | | Yes | |
| Observations | 20,215 | 20,215 | 20,215 |
| R-squared | 0.903 | 0.903 | 0.903 |
| F-statistic for $n = +1$ to $+4$ | 4.13*** | 3.93*** | 4.70*** |
| F-statistic for $n = -1$ to $-4$ | 0.66 | 1.11 | 1.04 |

Figure 4A: Coefficient on -(Z-score) × LE: % # Loans reduction

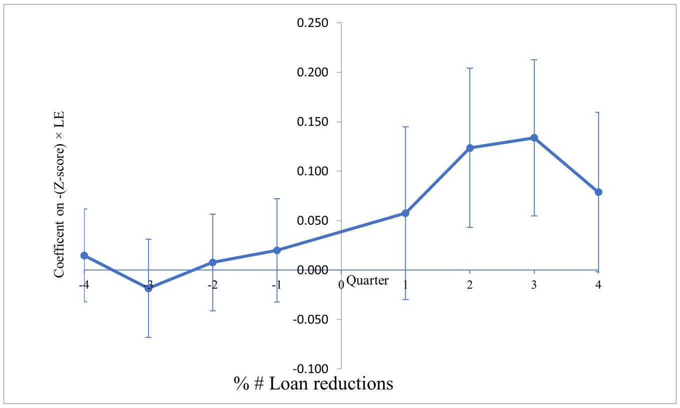


Figure 4B: Coefficient on -(Z-score) × LE: Lehman exposure

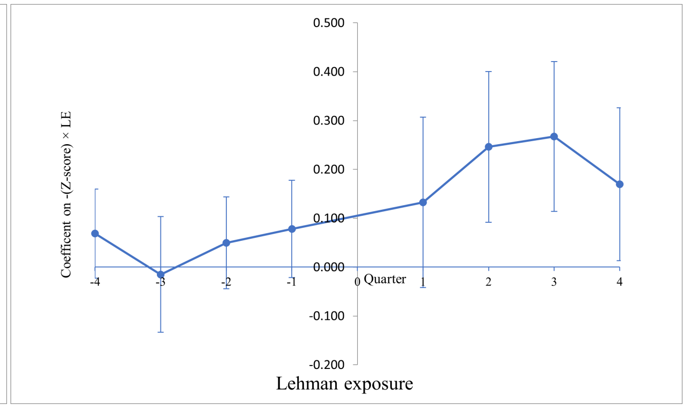


Figure 4C: Coefficient on -(Z-score) × LE: ABX exposure

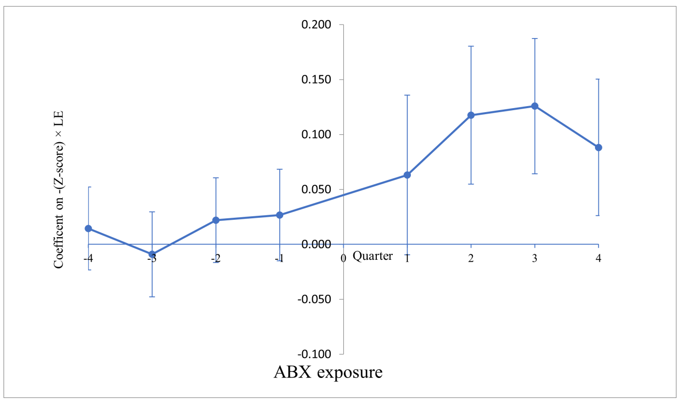


Figure 4: **Markup and credit risk: Dynamic effects of exposure to the financial crisis**

This figure plots the the point estimates of the coefficients on on -(Z-score) × LE, as in Table 8, and their 95% confidence intervals.

# Internet Appendix

## I.A. Omitted proofs in Section 2.3

### IA.1 Second-order condition in benchmark case ($F = 0$)

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

$$\frac{\partial^2 \bar{E}}{\partial i^2} = -K''(I+i) - \frac{\lambda x_2}{I^2} \frac{g'(u_O) - g(u_O)\frac{\delta''(u_O)}{\delta'(u_O)}}{[\delta'(u_O)]^2} < 0 \tag{IA.1}$$

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.2 Optimal hedging policy when $u_F \geq u_O$

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

$$p - K'(I+i) = V(u_F, i)\alpha K'(I+i)\ . \tag{IA.2}$$

Define $i^*$ is the firm'optimal hedging policy that satisfies (IA.2). The following assumption guarantees that a positive interior solution $i^*$ exists and $D(i^*, \bar{F}) > 0$ for sufficiently large $\bar{F}$:

**Assumption IA.1.** $p - K'(I) > (pI + x_2)\alpha K'(I)$ .

We first prove the following lemma:

**Lemma IA.1.** *If Assumption IA.1 holds and $\bar{F}$ is sufficiently large, then the first-order condition* (IA.2) *admits a unique and positive interior solution $i^*$ that maximizes $E$ subject to $D(i, \bar{F}) > 0$.*

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 IA.1 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 IA.1, since $K(I+i)$ is convex in $i$. For any $\bar{F} > 0$, the right hand-side of the first-order condition (IA.2) 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 (IA.2) decreases with $i$. The right hand-side of the first-order condition (IA.2) 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 (IA.2) 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 (IA.2) 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 (IA.2) is also the sufficient condition for the solution of the constrained maximization problem subject to $D(i, \bar{F}) > 0$, we have proved Lemma IA.1.

In what follows, we proof Lemma 2.1: 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.3 Optimal hedging policy when $u_F < u_O$

We begin this subsection by proving the following lemma:

**Lemma IA.2.** *If the production commitment $I$ is sufficiently high and $\frac{K'(I+\bar{i})}{I}$ is sufficiently low, then $\hat{i}^*$ that satisfies* (2.11) *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.

First, we show that $\hat{i}^*$ that satisfies the first-order condition (2.11) 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 $\kappa$ 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 (2.11), $\hat{S} = 0$ 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 2.2. $i^*$ 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, (2.11), with respect to $i$. The derivative of the left-hand side is $-K''(I+i) < 0$. The derivative of the right-hand side is

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

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 (2.11) decreases in $i$ and the right-hand side of Equation (2.11) increases in $i$. Since $\hat{i}^*$ satisfies the first-order condition in $u_O > u_F$ case, (2.11). We must have $\hat{i}^* > i^*$. Meanwhile, $\bar{i}$ satisfies the first-order condition (2.6):

$$
\begin{aligned}
p-K'(I+i^*) &= \lambda x_2\frac{g(u_O)}{I\delta'(u_O)} \\
&< V(u_F,i^*)h(u_F)K'(I+i^*)-\lambda x_2 h(u_F)K'(I+i^*)+\frac{\lambda x_2 g(u_O)}{[1-G(u_F)]I\delta'(u_O)}
\end{aligned}
\tag{IA.14}
$$

In a similar way, we can prove that $\bar{i} > \hat{i}^*$.

In what follows, we prove Lemma 2.3: 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 $\frac{\partial \hat{M}}{\partial \hat{i}^* \partial \bar{F}}$.

$$
\begin{aligned}
\frac{\partial^2 \hat{M}}{\partial \hat{i}^* \partial \bar{F}} &= [1-G(u_F)]\left[\begin{array}{c} pI\delta'(u_F)\frac{\partial u_F}{\partial \bar{F}}h(u_F)K'(I+\hat{i}^*)-[V(u_F,\hat{i}^*)-\lambda x_2]\frac{\partial h(u_F)}{\partial u_F}\frac{\partial u_F}{\partial \bar{F}}K'(I+i) \\ -\frac{\lambda x_2}{I}\frac{g(u_O)g(u_F)}{[1-G(u_F)]^2\delta'(u_O)}\frac{\partial u_F}{\partial \bar{F}} \end{array}\right] \\
&= [1-G(u_F)]\left[\begin{array}{c} pI\delta'(u_F)h(u_F)K'(I+i^*)-[V(u_F,i^*)-\lambda x_2]\frac{\partial h(u_F)}{\partial u_F}K'(I+i) \\ -\frac{\lambda x_2}{I}\frac{g(u_O)g(u_F)}{[1-G(u_F)]^2\delta'(u_O)} \end{array}\right]
\end{aligned}
\tag{IA.15}
$$

Since $u$ follows an exponential distribution, $\frac{\partial h(u_F)}{\partial u_F} = 0$. Thus, Equation (IA.15) 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.4 Optimal operational 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 $\bar{F} \le \bar{F}_{fb}$, 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 $D^*(\bar{F}_1) = 0$. This subsection 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 IA.1.** *If Lemma IA.2 holds, then*

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

*II. If $\bar{F}_{fb} < \bar{F} \le \bar{F}_0$, 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 $\bar{F} \ge \bar{F}_1$, the firm's optimal operational hedging policy is $i^*$.*

First of all, $\bar{i}$ in Appendix IA.1 is the optimal equity-maximizing hedging policy given the inherited net short-term debt level $\bar{F}$ is sufficiently low, i.e., $\bar{F} \le \bar{F}_{fb}$. $\bar{F}_{fb}$ 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:

$$\frac{\partial D}{\partial i} = K'(I + i) - \frac{1}{I\delta'(u_O)} \,, \tag{IA.16a}$$

$$\frac{\partial D}{\partial \bar{F}} = 1 \,. \tag{IA.16b}$$

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.3.**

$$\frac{dD^*}{d\bar{F}} > 0 \text{ } if \text{ } u_F(i^*) \geq u_O(i^*) \tag{IA.17a}$$

$$\frac{d\hat{D}^*}{d\bar{F}} > 0 \text{ } if \text{ } u_F(\hat{i}^*) \geq u_O(\hat{i}^*) \tag{IA.17b}$$

*Proof.* First we prove the following inequality:

$$\frac{dD^*}{d\bar{F}} = \frac{\partial D^*}{\partial \bar{F}} + \frac{\partial D^*}{\partial i^*}\frac{\partial i^*}{\partial \bar{F}} > 0 \tag{IA.18}$$

Using Equations (IA.16a) and (IA.16b) Inequality (IA.18) is equivalent to

$$\left[K'(I+i^*) - \frac{1}{I\delta'(u_O)}\right]\left(-\frac{\partial i^*}{\partial \bar{F}}\right) < 1 \tag{IA.19}$$

From Appendix IA.2, $\frac{\partial i^*}{\partial \bar{F}} = -\frac{\partial^2 M}{\partial i^* \partial \bar{F}} / \frac{\partial^2 M}{\partial i^{*2}}$. $\frac{\partial^2 M}{\partial i^* \partial \bar{F}}$ 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.19) is equivalent to

$$\frac{V(u_F, i^*)\frac{\partial h(u_F)}{\partial u_F}K'(I+i^*) - pI\delta'(u_F)h(u_F)K'(I+i^*)}{\left[\begin{array}{c} K''(I+i^*) + p[1-\delta'(u_F)IK'(I+i^*)]h(u_F)K'(I+i^*) \\ +V(u_F, i^*)\frac{\partial h(u_F)}{\partial u_F}[K'(I+i^*)]^2 + V(u_F, i^*)h(u_F)K''(I+i^*) \end{array}\right]} \frac{1 - I\delta'(u_O)K'(I+i^*)}{-I\delta'(u_O)} < 1 \tag{IA.20}$$

Algebraic simplification shows that the above inequality is equivalent to

$$\begin{aligned} &V(u_F, i^*)\frac{\partial h(u_F)}{\partial u_F}K'(I+i^*) + pI\left[\delta'(u_O) - \delta'(u_F)\right]h(u_F)K'(I+i^*) \\ &< \left[1 + V(u_F, i^*)h(u_F)\right]K''(I+i^*)\left[-I\delta'(u_O)\right] \end{aligned} \tag{IA.21}$$

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.21) 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.21) is (weakly) smaller than zero. The right-hand side of Inequality (IA.21) is strictly greater than zero. Therefore, Inequality (IA.21) holds and $\frac{dD^*}{d\bar{F}} > 0$.

Now we prove the following inequality:

$$\frac{d\hat{D}^*}{d\bar{F}} = \frac{\partial \hat{D}^*}{\partial \bar{F}} + \frac{\partial \hat{D}^*}{\partial \hat{i}^*}\frac{\partial \hat{i}^*}{\partial \bar{F}} > 0 \tag{IA.22}$$

Inequality (IA.18) is equivalent to

$$\left[K'(I+\hat{i}^*) - \frac{1}{I\delta'(u_O)}\right]\left(-\frac{\partial \hat{i}^*}{\partial \bar{F}}\right) < 1 \tag{IA.23}$$

From Appendix IA.3, $\frac{\partial \hat{i}^*}{\partial \bar{F}} = -\frac{\partial^2 \hat{M}}{\partial \hat{i}^* \partial \bar{F}} / \frac{\partial^2 \hat{M}}{\partial \hat{i}^{*2}}$. $\frac{\partial^2 \hat{M}}{\partial i^* \partial \bar{F}}$ is given by Equation (IA.15). $\frac{\partial^2 \hat{M}}{\partial \hat{i}^{*2}}$ 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.23) is equivalent to

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

Algebraic simplification shows that the above inequality is equivalent to

$$\begin{aligned} &[V(u_F,\hat{i}^*) - \lambda x_2]\frac{\partial h(u_F)}{\partial u_F}K'(I+\hat{i}^*) + pI\left[\delta'(u_O) - \delta'(u_F)\right]h(u_F)K'(I+\hat{i}^*) + \frac{\lambda x_2}{I}\frac{g(u_O)g(u_F)}{[1-G(u_F)]^2\delta'(u_O)} \\ &< \left[1 + [V(u_F,\hat{i}^*) - \lambda x_2]h(u_F)\right]K''(I+\hat{i}^*)\left[-I\delta'(u_O)\right] - \lambda x_2\frac{g'(u_O)\delta'(u_O) - g(u_O)\delta''(u_O)}{[1-G(u_F)][\delta'(u_O)]^2 I} \end{aligned} \tag{IA.25}$$

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.25) 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.25) is strictly greater than zero. Therefore, to show that Inequality

(IA.25) holds, we need to show that:

$$\frac{\lambda x_2}{I}\frac{g(u_O)g(u_F)}{[1-G(u_F)]^2\delta'(u_O)} < -\lambda x_2\frac{g'(u_O)\delta'(u_O)-g(u_O)\delta''(u_O)}{[1-G(u_F)][\delta'(u_O)]^2 I} \tag{IA.26}$$

Or, equivalently,

$$\begin{aligned}
&\frac{\lambda x_2}{I}\frac{g(u_O)g(u_F)}{[1-G(u_F)]^2\delta'(u_O)} + \lambda x_2\frac{g'(u_O)\delta'(u_O)-g(u_O)\delta''(u_O)}{[1-G(u_F)][\delta'(u_O)]^2 I} < 0\\
\Leftrightarrow\ &\frac{\lambda x_2}{I[1-G(u_F)]\delta'(u_O)}\left[\frac{g(u_O)g(u_F)}{[1-G(u_F)]} + \frac{g'(u_O)\delta'(u_O)-g(u_O)\delta''(u_O)}{\delta'(u_O)}\right] < 0\\
\Leftrightarrow\ &\frac{g(u_O)g(u_F)}{[1-G(u_F)]} + \frac{g'(u_O)\delta'(u_O)-g(u_O)\delta''(u_O)}{\delta'(u_O)} > 0
\end{aligned} \tag{IA.27}$$

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.27) is equivalent to

$$\frac{\delta''(u_O)}{\delta'(u_O)} < 0 \tag{IA.28}$$

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 IA.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 IA.1,$D^* > 0$ if $\bar{F} \geq \bar{F}_M$. From Lemma 2.2, 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.3, $\frac{d\hat{D}^*}{d\bar{F}} > 0$ 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 2.2, $\hat{i}^* > i^*$ 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.2, 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 of $i$ 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.2, equity value $E$ decreases in $i$ for $i > i^*$. Meanwhile, the feasible set of $i$ 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.3, $\hat{E}$ increases in $i$ for $i < \hat{i}^*$. 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.3, $\hat{E}$ 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 2.1. From Proposition IA.1 and Lemma 2.1, when $\bar{F} > \bar{F}_1$, $i^{**} = i^*$ and thus decreases in $\bar{F}$. Similarly, from Proposition IA.1 and Lemma 2.3, 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.16a) and (IA.16b), $\frac{\partial \tilde{i}}{\partial \bar{F}} < 0$. 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 $\bar{F}$.

## IA.5 Partial pledgeability

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

$$E_{PP} = \int_{u_{F,PP}}^{\infty} \Big[(u - u_{F,PP}) - \tau p[(1-\delta(u_{F,PP}))I + i] + p[(1-\delta(u))I+i] + x_2\Big] g(u)du \ . \quad \text{(IA.29)}$$

The value of equity when $u_{F,PP} < u_O$ is $E_{PP} - \int_{u_F}^{u_O} \lambda x_2 g(u)du$.

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:

$$p - K'(I + i^*_{PP}) = V(u_{F,PP}, i^*_{PP})\ h(u_{F,PP})\ \frac{[K'(I + i^*_{PP}) - \tau p]}{[1 - \tau p \delta'(u_{F,PP})I]}\ , \quad \text{(IA.30)}$$

$$p - K'(I + \hat{i}^*_{PP}) = \Big[V(u_{F,PP}, \hat{i}^*_{PP}) - \lambda x_2\Big]\ h(u_{F,PP})\ \frac{[K'(I + \hat{i}^*_{PP}) - \tau p]}{[1 - \tau p \delta'(u_{F,PP})I]} + \frac{\lambda x_2 g(u_O)}{[1 - G(u_{F,PP})]I\delta'(u_O)}\ . \quad \text{(IA.31)}$$

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

$$\bar{F}_{fb,PP} + K(I + \bar{i}_{PP}) = \tau * p * \bar{i}_{PP}\ . \quad \text{(IA.32)}$$

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 IA.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., $\tau < \bar{\tau} < 1$:[33]

**Proposition IA.2.** *There exists $\bar{\tau} < 1$ such that if $\tau < \bar{\tau}$, then*

[33] The proofs of Proposition IA.2 and Proposition 3.1 are similar to the base case although the algebra is much more involved. The proofs are available upon request.

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

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

*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* $i^*_{PP}$*.*

## I.B. Empirical results with leverage

In this appendix, we report results using total leverage, defined as (long-term debt($DLTTQ$)+ short-term debt($DLCQ$))/total assets($ATQ$), as well as long-term debt maturing in the next 2 years, defined as ($DD1 + DD2$) according to the most recent fiscal year-end divided by total assets and remaining long-term leverage, defined as ($DLTTQ - DD2$) divided by total assets, instead of -(Z-score) as our explanatory variables.

Table IB.1: **Summary statistics** — Leverage, Long-term leverage maturing in the next 2 years and Remaining long-term leverage

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. 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.

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 |
|---|---|---|---|---|---|---|
| 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 |

Table IB.2: **Markup and leverage**

Estimation of the relationship between Markup 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. 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, and Sales/total sales. All explanatory variables are lagged by one quarter. The regressions include firm and Fama-French 38 Industry × year-quarter fixed effects. Standard errors are clustered at firm and Fama-French 38 Industry × year-quarter levels. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively.

| VARIABLES | Markup | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Financial leverage | 0.036*** | | |
| | (0.010) | | |
| Long-term debt maturing in the next 2 years/total assets | | 0.070*** | 0.041** |
| | | (0.017) | (0.017) |
| Remaining long-term leverage | | 0.037*** | 0.0089 |
| | | (0.011) | (0.011) |
| -(Z-score) | | | 0.0036*** |
| | | | (0.00060) |
| Firm fixed effects | | Yes | |
| Industry × year-quarter fixed effects | | Yes | |
| Observations | 582,933 | 504,527 | 477,771 |
| R-squared | 0.623 | 0.640 | 0.646 |

Table IB.3: **Operational hedging and credit risk: NBER recessions**

Regressions of Markup, Inventory and Supply chain hedging on firms' Leverage, Maturing LT leverage and Remaining LT leverage that interact with NBER recession years. We exclude the Covid-related recession during the first two quarters of 2020. *Recession* = 1 if the quarter is classified as NBER recession, and = 0 otherwise. For each recession, the values of Leverage, Short-term and Reamining long-term leverage, as well as 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 5. Panel A examines markup. Panel B examines inventory- sales ratio. Panels C and D examine the two measures of supply chain hedging (SCH) variables — Supply chain hedging index (SCH index) and Supply chain hedging ranking (SCH ranking), respectively. The variable definitions are in Table 2. The regressions include firm and Fama-French 38 Industry × 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: *SCH index* | | Panel D: *SCH ranking* | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Leverage × recession | 0.032** | | -0.033*** | | 0.053 | | 0.012 | |
| | (0.013) | | (0.012) | | (0.073) | | (0.014) | |
| Leverage | 0.035*** | | -0.031*** | | 0.128** | | 0.027** | |
| | (0.010) | | (0.010) | | (0.061) | | (0.011) | |
| Maturing LT leverage × recession | | 0.069* | | -0.039 | | 0.044 | | 0.044 |
| | | (0.035) | | (0.039) | | (0.254) | | (0.047) |
| Maturing LT leverage | | 0.066*** | | -0.055*** | | 0.104 | | 0.013 |
| | | (0.017) | | (0.018) | | (0.116) | | (0.021) |
| Remaining LT leverage × recession | | 0.010 | | -0.012 | | 0.008 | | -0.001 |
| | | (0.015) | | (0.014) | | (0.083) | | (0.015) |
| Remaining LT leverage | | 0.039*** | | -0.022** | | 0.108 | | 0.021* |
| | | (0.012) | | (0.011) | | (0.070) | | (0.012) |
| Control variables | | | | Yes | | | | |
| Firm fixed effects | | | | Yes | | | | |
| Industry × year-quarter fixed effects | | | | Yes | | | | |
| Observations | 572,405 | 496,046 | 560,384 | 486,235 | 116,205 | 102,824 | 116,205 | 102,824 |
| R-squared | 0.626 | 0.641 | 0.735 | 0.751 | 0.862 | 0.866 | 0.814 | 0.820 |

Table IB.4: **Operational hedging and credit risk: Exposure to the financial crisis**

Regressions of Markup, Inventory- sales ratio and supply chain hedging on firms' Leverage, Maturing LT leverage and Remaining LT 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 Leverage, Maturing LT leverage and Remaining LT leverage are as of the end of 2007. The firm-level control variables, as in Table 5, 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 hedging (SCH) — Supply chain hedging index (SCH index) and Supply chain hedging ranking (SCH ranking), respectively. The variable definitions are in Table 2. The regressions include firm and Fama-French 38 Industry $\times$ year-quarter 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) |
| Leverage × lender exposure | 0.468 | | 0.582 | | 0.373 | |
| | (0.323) | | (0.626) | | (0.293) | |
| Maturing LT leverage × lender exposure | | 1.785 | | 2.850 | | 1.346 |
| | | (1.183) | | (2.100) | | (0.992) |
| Remaining LT leverage × lender exposure | | 0.353 | | 0.398 | | 0.269 |
| | | (0.389) | | (0.742) | | (0.348) |
| Lender exposure | -0.899** | -1.010** | -1.153 | -0.969 | -0.927** | -1.063** |
| | (0.454) | (0.494) | (0.729) | (0.779) | (0.403) | (0.435) |
| Control variables | Yes | | | | | |
| Control variables × lender exposure | Yes | | | | | |
| Firm fixed effects | Yes | | | | | |
| Industry × year-quarter fixed effects | Yes | | | | | |
| Observations | 21,827 | 19,595 | 21,827 | 19,595 | 21,827 | 19,595 |
| R-squared | 0.901 | 0.902 | 0.900 | 0.902 | 0.901 | 0.903 |

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) |
| Leverage × lender exposure | -1.693*** | | -2.705** | | -1.176*** | |
| | (0.537) | | (1.063) | | (0.444) | |
| Maturing LT leverage × lender exposure | | 1.916 | | 1.894 | | 2.389 |
| | | (2.702) | | (4.383) | | (2.350) |
| Remaining LT leverage × lender exposure | | -1.333** | | -1.227 | | -0.807* |
| | | (0.556) | | (1.075) | | (0.471) |
| Lender exposure | 1.384 | 1.068 | 0.365 | -2.307 | 0.924 | 0.381 |
| | (1.076) | (1.069) | (2.163) | (1.698) | (0.983) | (1.030) |
| Control variables | Yes | | | | | |
| Control variables × lender exposure | Yes | | | | | |
| Firm fixed effects | Yes | | | | | |
| Industry × year-quarter fixed effects | Yes | | | | | |
| Observations | 21,377 | 19,206 | 21,377 | 19,206 | 21,377 | 19,206 |
| R-squared | 0.902 | 0.906 | 0.902 | 0.906 | 0.902 | 0.906 |

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

| | % # Loans reduction | | Lehman exposure | | ABX exposure | |
|---|---|---|---|---|---|---|
| VARIABLES | *Supply chain hedging index* | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Leverage × lender exposure | -2.938 | | -12.287** | | -5.557** | |
| | (2.943) | | (5.585) | | (2.550) | |
| Maturing LT leverage × lender exposure | | 2.373 | | 13.639 | | 0.067 |
| | | (11.609) | | (20.798) | | (9.748) |
| Remaining LT leverage × lender exposure | | -3.064 | | -13.335** | | -6.191** |
| | | (3.331) | | (5.912) | | (2.912) |
| Lender exposure | 0.012 | -0.458 | 20.283** | 21.242** | 11.773** | 13.614*** |
| | (5.610) | (6.037) | (10.215) | (10.746) | (4.580) | (4.746) |
| Control variables | Yes | | | | | |
| Control variables × lender exposure | Yes | | | | | |
| Firm fixed effects | Yes | | | | | |
| Industry × year-quarter fixed effects | Yes | | | | | |
| Observations | 14,353 | 12,935 | 14,353 | 12,935 | 14,353 | 12,935 |
| R-squared | 0.939 | 0.939 | 0.939 | 0.939 | 0.939 | 0.939 |

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

| | % # Loans reduction | | Lehman exposure | | ABX exposure | |
|---|---|---|---|---|---|---|
| VARIABLES | *Supply chain hedging ranking* | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Leverage × lender exposure | -0.600 | | -2.430** | | -1.069** | |
| | (0.575) | | (1.082) | | (0.498) | |
| Maturing LT leverage × lender exposure | | 1.085 | | 3.177 | | 0.372 |
| | | (2.192) | | (3.905) | | (1.866) |
| Remaining LT leverage × lender exposure | | -0.689 | | -2.704** | | -1.211** |
| | | (0.652) | | (1.155) | | (0.572) |
| Lender exposure | -0.224 | -0.234 | 3.353* | 3.598* | 1.918** | 2.265** |
| | (1.076) | (1.153) | (1.944) | (2.021) | (0.921) | (0.950) |
| Control variables | Yes | | | | | |
| Control variables × lender exposure | Yes | | | | | |
| Firm fixed effects | Yes | | | | | |
| Industry × year-quarter fixed effects | Yes | | | | | |
| Observations | 14,353 | 12,935 | 14,353 | 12,935 | 14,353 | 12,935 |
| R-squared | 0.914 | 0.915 | 0.914 | 0.915 | 0.914 | 0.915 |

Table IB.5: **Markup and credit risk:**
**Dynamic effects of exposure to the financial crisis: Leverage**

Regressions of Markup on firms' Leverage that interacts with the extent of lender exposures to the 2008 financial crisis in each quarter $D_n$, $n = -1, -2, -3, -4, +1, +2, +3, +4, +5 + (+5 — +8)$ 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 Leverage are as of the end of 2007. The firm-level control variables, as in Table 5, 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 *Leverage* and the size of *LE* for quarters $D_n$. The regressions include firm and Fama-French 38 Industry × year-quarter fixed effects. Standard errors are clustered by firm. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively.

| | % # Loans reduction | Lehman exposure | ABX exposure |
|---|---|---|---|
| VARIABLES | | *Markup* | |
| *Leverage* × *LE*, $D_{-4}$ | 0.246 | 0.507 | 0.153 |
| | (0.334) | (0.603) | (0.292) |
| *Leverage* × *LE*, $D_{-3}$ | -0.586 | -1.197 | -0.474 |
| | (0.365) | (0.842) | (0.309) |
| *Leverage* × *LE*, $D_{-2}$ | -0.218 | -0.643 | -0.075 |
| | (0.375) | (0.713) | (0.326) |
| *Leverage* × *LE*, $D_{-1}$ | 0.161 | 0.019 | 0.212 |
| | (0.376) | (0.662) | (0.330) |
| *Leverage* × *LE*, $D_1$ | 1.114** | 1.764* | 1.017** |
| | (0.517) | (0.988) | (0.463) |
| *Leverage* × *LE*, $D_2$ | 0.602 | 0.795 | 0.509 |
| | (0.440) | (0.810) | (0.396) |
| *Leverage* × *LE*, $D_3$ | 0.738* | 0.991 | 0.562 |
| | (0.420) | (0.802) | (0.366) |
| *Leverage* × *LE*, $D_4$ | -0.151 | -0.510 | -0.097 |
| | (0.440) | (0.841) | (0.385) |
| *Leverage* × *LE*, $D_{+5+}$ | 0.238 | 0.007 | 0.178 |
| | (0.408) | (0.768) | (0.368) |
| Lender exposure, $D_n$ | | Yes | |
| Control variables | | Yes | |
| Control variables × lender exposure | | Yes | |
| Firm fixed effects | | Yes | |
| Industry × year-quarter fixed effects | | Yes | |
| Observations | 21,076 | 21,076 | 21,076 |
| R-squared | 0.898 | 0.898 | 0.899 |
| F-statistic for $n = +1$ to $+4$ | 4.44*** | 2.96** | 3.76*** |
| F-statistic for $n = -1$ to $-4$ | 1.57 | 1.16 | 1.38 |

Table IB.6: **Markup and credit risk:**
**Dynamic effects of exposure to the financial crisis: Maturing LT and Remaining LT leverage**

Regressions of Markup on firms' Maturing LT leverage and Remaining LT leverage that interact with the extent of lender exposures to the 2008 financial crisis in each quarter $D_n$, $n = -1, -2, -3, -4, +1, +2, +3, +4, +5 + (+5 — \ + 8)$ 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 Maturing LT leverage and Remaining LT leverage are as of the end of 2007. The firm-level control variables, as in Table 5, 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 Maturing LT leverage, as well as Remaining LT leverage, and the size of $LE$ for quarters $D_n$. The regressions include firm and Fama-French 38 Industry $\times$ year-quarter fixed effects. Standard errors are clustered by firm. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively.

| | % # Loans reduction | Lehman exposure | ABX exposure |
|---|---|---|---|
| VARIABLES | | *Markup* | |
| *Maturing LT leverage* × *LE*, $D_{-4}$ | -0.815 | -0.563 | -0.322 |
| | (1.251) | (2.288) | (0.993) |
| *Remaining LT leverage* × *LE*, $D_{-4}$ | 0.181 | 0.471 | 0.074 |
| | (0.386) | (0.683) | (0.340) |
| *Maturing LT leverage* × *LE*, $D_{-3}$ | -0.617 | 0.526 | -0.333 |
| | (1.267) | (2.339) | (1.057) |
| *Remaining LT leverage* × *LE*, $D_{-3}$ | -0.684** | -1.050 | -0.595* |
| | (0.341) | (0.665) | (0.305) |
| *Maturing LT leverage* × *LE*, $D_{-2}$ | -0.064 | 1.951 | 0.357 |
| | (1.212) | (2.172) | (1.026) |
| *Remaining LT leverage* × *LE*, $D_{-2}$ | -0.583 | -1.164 | -0.412 |
| | (0.414) | (0.736) | (0.365) |
| *Maturing LT leverage* × *LE*, $D_{-1}$ | -0.034 | 0.769 | -0.050 |
| | (1.271) | (2.153) | (1.051) |
| *Remaining LT leverage* × *LE*, $D_{-1}$ | 0.001 | -0.050 | 0.051 |
| | (0.412) | (0.654) | (0.367) |
| *Maturing LT leverage* × *LE*, $D_1$ | 3.576** | 6.054** | 3.060** |
| | (1.757) | (2.976) | (1.484) |
| *Remaining LT leverage* × *LE*, $D_1$ | 0.510 | 0.748 | 0.516 |
| | (0.614) | (1.155) | (0.550) |
| *Maturing LT leverage* × *LE*, $D_2$ | -0.273 | -0.316 | -0.305 |
| | (1.764) | (3.021) | (1.511) |
| *Remaining LT leverage* × *LE*, $D_2$ | 0.559 | 0.815 | 0.456 |
| | (0.503) | (0.907) | (0.449) |
| *Maturing LT leverage* × *LE*, $D_3$ | 1.568 | 3.285 | 1.464 |
| | (1.551) | (2.521) | (1.250) |
| *Remaining LT leverage* × *LE*, $D_3$ | 0.653 | 0.963 | 0.466 |
| | (0.479) | (0.890) | (0.417) |
| *Maturing LT leverage* × *LE*, $D_4$ | 1.535 | 3.192 | 1.413 |
| | (1.562) | (2.589) | (1.268) |
| *Remaining LT leverage* × *LE*, $D_4$ | -0.322 | -0.608 | -0.300 |
| | (0.479) | (0.890) | (0.427) |
| *Maturing LT leverage* × *LE*, $D_{+5+}$ | 1.571 | 3.281 | 1.197 |
| | (1.423) | (2.377) | (1.192) |
| *Remaining LT leverage* × *LE*, $D_{+5+}$ | 0.040 | -0.220 | -0.015 |
| | (0.456) | (0.850) | (0.410) |
| | | | |
| Lender exposure, $D_n$ | | Yes | |
| Control variables | | Yes | |
| Control variables × lender exposure | | Yes | |
| Firm fixed effects | | Yes | |
| Industry × year-quarter fixed effects | | Yes | |
| | | | |
| Observations | 18,962 | 18,962 | 18,962 |
| R-squared | 0.900 | 0.900 | 0.900 |
| F-statistic for $n = +1$ (Maturing LT debt) to $+4$ | 1.73 | 1.70 | 1.74 |
| F-statistic for $n = -1$ (Maturing LT debt) to $-4$ | 0.11 | 0.38 | 0.16 |
| F-statistic for $n = +1$ (Remaining LT debt) to $+4$ | 3.00** | 2.26* | 2.38* |
| F-statistic for $n = -1$ (Remaining LT debt) to $-4$ | 1.57 | 1.41 | 1.36 |

# I.C. Empirical results with interaction terms between liquidity and market power

In this appendix, we augment our baseline regressions in the main text and in Appendix I.B with the interaction terms between market power variables: Dummy variable for the top 3 industry seller, Sales/industry sales, Herfindahl index, and -(Z-score), Financial Leverage, Long-term debt maturing in the next two years/total assets. All the variable definitions are the same as of respective definitions in Table 2 and Table IB.1. We also conduct a split-sample analyses according to the market power measures. The results are qualitatively similar and are available upon request.

Table IC.1: **Markup, liquidity demand and market power**

Estimation of the relationship between Markup, liquidity demand variables: -(Z-score), Leverage, Maturing long-term leverage, the market power, proxied by Dummy variable for the top 3 industry seller (Panel A), Sales/industry sales (Panel B), Herfindahl index (Panel C), and the interaction terms between each of the liquidity demand variables and the market power. The regressions include firm and Fama-French 38 Industry × year-quarter fixed effects. Control variables are the same as Table 5. Standard errors are clustered at firm and year-quarter levels. ∗, ∗∗, ∗ ∗ ∗ denote significance below 10%, 5%, and 1% levels, respectively.

| VARIABLES | | *Markup* | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Panel A: Dummy variable for top-3 industry seller | | | |
| Top 3 industry seller × -(z-score) | -0.0030** | | |
| | (0.0013) | | |
| Top 3 industry seller × leverage | | 0.013 | |
| | | (0.021) | |
| Top 3 industry seller × ST leverage | | | 0.092 |
| | | | (0.062) |
| Top 3 industry seller × Remaining LT leverage | | | 0.00088 |
| | | | (0.023) |
| -(Z-score) | 0.0033*** | | |
| | (0.00054) | | |
| Financial leverage | | 0.036*** | |
| | | (0.010) | |
| Long-term debt maturing in the next 2 years/total assets | | | 0.070*** |
| | | | (0.017) |
| Remaining long-term leverage | | | 0.037*** |
| | | | (0.011) |
| Top 3 industry seller | -0.00080 | 0.0021 | 0.0010 |
| | (0.0067) | (0.0080) | (0.0084) |
| Observations | 571,135 | 582,933 | 504,527 |
| R-squared | 0.630 | 0.623 | 0.640 |

| Panel B: Sales/industry sales | | | |
|---|---|---|---|
| Sales/industry sales × -(z-score) | -0.071*** | | |
| | (0.019) | | |
| Sales/industry sales × leverage | | 0.0074 | |
| | | (0.221) | |
| Sales/industry sales × ST leverage | | | 0.280 |
| | | | (0.548) |
| Sales/industry sales | | | -0.036 |
| × Remaining LT leverage | | | (0.248) |
| -(Z-score) | 0.0034*** | | |
| | (0.00054) | | |
| Financial leverage | | 0.036*** | |
| | | (0.011) | |
| Long-term debt maturing in | | | 0.069*** |
| the next 2 years/total assets | | | (0.018) |
| Remaining long-term leverage | | | 0.037*** |
| | | | (0.012) |
| Sales/industry sales | -0.799*** | -0.528*** | -0.463*** |
| | (0.135) | (0.146) | (0.148) |
| Observations | 571,135 | 582,933 | 504,527 |
| R-squared | 0.630 | 0.623 | 0.640 |

| Panel C: Herfindahl index | | | |
|---|---|---|---|
| Herfindahl index × -(z-score) | -0.0092** | | |
| | (0.0039) | | |
| Herfindahl index × leverage | | -0.156* | |
| | | (0.089) | |
| Herfindahl index × ST leverage | | | 0.099 |
| | | | (0.165) |
| Herfindahl index | | | -0.120 |
| × Remaining LT leverage | | | (0.099) |
| -(Z-score) | 0.0039*** | | |
| | (0.00064) | | |
| Financial leverage | | 0.046*** | |
| | | (0.014) | |
| Long-term debt maturing in | | | 0.064*** |
| the next 2 years/total assets | | | (0.023) |
| Remaining long-term leverage | | | 0.045*** |
| | | | (0.015) |
| Remaining long-term leverage | | | 0.045*** |
| | | | (0.015) |
| Observations | 571,135 | 582,933 | 504,527 |
| R-squared | 0.630 | 0.623 | 0.640 |
| Control variables | | Yes | |
| Firm fixed effects | | Yes | |
| Industry × year-quarter fixed effects | | Yes | |

Table IC.2: **Markup, liquidity demand and market power: NBER recessions**

Regression of Markup on firms' liquidity demand, NBER recessions, market power and interaction terms among the three characteristics. We augment the regression models in Table 6 and Table IB.3 with the liquidity demand variables × NBER recession dummy × market power variables, liquidity demand variables × market power variables, and NBER recession dummy × market power variables. The regressions include firm and Fama-French 38 Industry × year-quarter fixed effects. Control variables are the same as Table 6 and Table IB.3. Standard errors are clustered at firm and year-quarter levels. ∗, ∗∗, ∗ ∗ ∗ denote significance below 10%, 5%, and 1% levels, respectively.

| VARIABLES | | | *Markup* | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Top 3 industry seller × -(z-score) × Recession | -0.002 | | | | | | | | |
| | (0.002) | | | | | | | | |
| Top 3 industry seller × leverage × Recession | | -0.049** | | | | | | | |
| | | (0.025) | | | | | | | |
| Top 3 industry seller × ST leverage × Recession | | | -0.166* | | | | | | |
| | | | (0.093) | | | | | | |
| Top 3 industry seller × Remaining LT leverage × Recession | | | -0.058* | | | | | | |
| | | | (0.030) | | | | | | |
| Sales/industry sales × -(z-score) × Recession | | | | 0.000 | | | | | |
| | | | | (0.019) | | | | | |
| Sales/industry sales × leverage × Recession | | | | | -0.635** | | | | |
| | | | | | (0.265) | | | | |
| Sales/industry sales × ST leverage × Recession | | | | | | -1.218 | | | |
| | | | | | | (0.903) | | | |
| Sales/industry sales × Remaining LT leverage × Recession | | | | | | -0.647* | | | |
| | | | | | | (0.360) | | | |
| Herfindahl index × -(z-score) × Recession | | | | | | | -0.007 | | |
| | | | | | | | (0.009) | | |
| Herfindahl index × leverage × Recession | | | | | | | | -0.514** | |
| | | | | | | | | (0.208) | |
| Herfindahl index × ST leverage × Recession | | | | | | | | | 0.136 |
| | | | | | | | | | (0.683) |
| Herfindahl index × Remaining LT leverage × Recession | | | | | | | | | -0.649** |
| | | | | | | | | | (0.300) |
| -(Z-score) × Recession | 0.002*** | | | 0.002*** | | | 0.002** | | |
| | (0.001) | | | (0.001) | | | (0.001) | | |
| Leverage × Recession | | 0.033** | | | 0.036*** | | | 0.064*** | |
| | | (0.013) | | | (0.014) | | | (0.022) | |
| ST leverage × Recession | | | 0.070** | | | 0.073* | | | 0.059 |
| | | | (0.035) | | | (0.037) | | | (0.055) |
| Remaining LT leverage × Recession | | | 0.011 | | | 0.014 | | | 0.051* |
| | | | (0.016) | | | (0.017) | | | (0.027) |
| Liquidity demand variables × market power | | | | | Yes | | | | |
| Market power × Recession | | | | | Yes | | | | |
| Liquidity demand variables | | | | | Yes | | | | |
| Control variables | | | | | Yes | | | | |
| Firm fixed effects | | | | | Yes | | | | |
| Industry × year-quarter fixed effects | | | | | Yes | | | | |
| Observations | 560,911 | 572,405 | 496,046 | 560,911 | 572,405 | 496,046 | 560,911 | 572,405 | 496,046 |
| R-squared | 0.632 | 0.626 | 0.641 | 0.632 | 0.626 | 0.641 | 0.632 | 0.626 | 0.641 |

Table IC.3: **Operational hedging, liquidity demand and market power: Exposure to the financial crisis**

Regressions of Markup on firms' liquidity demands, the extent of exposures to the 2008 financial crisis, market power and interaction terms among the three characteristics. We augmented the regression models in Table 7 and Table IB.4 with liquidity demand variables × lender exposure × market power variables and lender exposure × market power variables.[34] The variable definitions are in Table 2. The regressions include firm and Fama-French 38 Industry × year-quarter fixed effects. Standard errors are clustered by firm. $*$, $**$, $***$ denote significance below 10%, 5%, and 1% levels, respectively.

Panel A: % # Loans reduction

| VARIABLES | | | | | *Markup* | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Top 3 industry seller × -(z-score) × Exposure | 0.052 | | | | | | | | |
| | (0.055) | | | | | | | | |
| Top 3 industry seller × leverage × Exposure | | 1.365 | | | | | | | |
| | | (1.105) | | | | | | | |
| Top 3 industry seller × maturing LT leverage × Exposure | | | -2.183 | | | | | | |
| | | | (4.331) | | | | | | |
| Top 3 industry seller × Remaining LT leverage × Exposure | | | 2.000* | | | | | | |
| | | | (1.193) | | | | | | |
| Sales/industry sales × -(z-score) × Exposure | | | | 0.711 | | | | | |
| | | | | (0.528) | | | | | |
| Sales/industry sales × leverage × Exposure | | | | | 2.850 | | | | |
| | | | | | (11.661) | | | | |
| Sales/industry sales × maturing LT leverage × Exposure | | | | | | -32.067 | | | |
| | | | | | | (43.388) | | | |
| Sales/industry sales × Remaining LT leverage × Exposure | | | | | | 13.028 | | | |
| | | | | | | (11.751) | | | |
| Herfindahl index × -(z-score) × Exposure | | | | | | | -0.048 | | |
| | | | | | | | (0.544) | | |
| Herfindahl index × leverage × Exposure | | | | | | | | -0.714 | |
| | | | | | | | | (5.397) | |
| Herfindahl index × maturing LT leverage × Exposure | | | | | | | | | 9.729 |
| | | | | | | | | | (29.209) |
| Herfindahl index × Remaining LT leverage × Exposure | | | | | | | | | 3.144 |
| | | | | | | | | | (6.334) |
| -(Z-score) × lender exposure | 0.086** | | | 0.082** | | | 0.089** | | |
| | (0.034) | | | (0.034) | | | (0.043) | | |
| Leverage × lender exposure | | 0.433 | | | 0.411 | | | 0.557 | |
| | | (0.325) | | | (0.349) | | | (0.417) | |
| Maturing LT leverage × lender exposure | | | 1.763 | | | 1.885 | | | 1.219 |
| | | | (1.198) | | | (1.331) | | | (2.068) |
| Remaining LT leverage × lender exposure | | | 0.301 | | | 0.234 | | | 0.324 |
| | | | (0.393) | | | (0.420) | | | (0.528) |
| Lender exposure | -0.746* | -0.904** | -1.001** | -0.759* | -0.899** | -1.014** | -0.741* | -0.912** | -1.047** |
| | (0.447) | (0.454) | (0.495) | (0.449) | (0.454) | (0.496) | (0.446) | (0.455) | (0.497) |
| Liquidity demand × market power | | | | | Yes | | | | |
| Control variables | | | | | Yes | | | | |
| Control variables × lender exposure | | | | | Yes | | | | |
| Firm fixed effects | | | | | Yes | | | | |
| Industry × year-quarter fixed effects | | | | | Yes | | | | |
| Observations | 20,926 | 21,827 | 19,595 | 20,926 | 21,827 | 19,595 | 20,926 | 21,827 | 19,595 |
| R-squared | 0.905 | 0.901 | 0.902 | 0.905 | 0.901 | 0.902 | 0.905 | 0.901 | 0.902 |

## Panel B: Lehman exposure

| VARIABLES | Markup | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Top 3 industry seller × -(z-score) × Exposure | 0.108 | | | | | | | | |
| | (0.119) | | | | | | | | |
| Top 3 industry seller × leverage × Exposure | | 4.034** | | | | | | | |
| | | (1.865) | | | | | | | |
| Top 3 industry seller × maturing LT leverage × Exposure | | | -4.014 | | | | | | |
| | | | (7.886) | | | | | | |
| Top 3 industry seller × Remaining LT leverage × Exposure | | | 5.224** | | | | | | |
| | | | (2.192) | | | | | | |
| Sales/industry sales × -(z-score) × Exposure | | | | 1.582 | | | | | |
| | | | | (1.117) | | | | | |
| Sales/industry sales × leverage × Exposure | | | | | 15.882 | | | | |
| | | | | | (18.187) | | | | |
| Sales/industry sales × maturing LT leverage × Exposure | | | | | | -47.922 | | | |
| | | | | | | (76.901) | | | |
| Sales/industry sales × Remaining LT leverage × Exposure | | | | | | 28.194 | | | |
| | | | | | | (20.427) | | | |
| Herfindahl index × -(z-score) × Exposure | | | | | | | -0.772 | | |
| | | | | | | | (1.028) | | |
| Herfindahl index × leverage × Exposure | | | | | | | | 4.700 | |
| | | | | | | | | (7.235) | |
| Herfindahl index × maturing LT leverage × Exposure | | | | | | | | | 21.419 |
| | | | | | | | | | (48.908) |
| Herfindahl index × Remaining LT leverage × Exposure | | | | | | | | | 10.078 |
| | | | | | | | | | (8.439) |
| -(Z-score) × lender exposure | 0.163** | | | 0.155** | | | 0.202** | | |
| | (0.069) | | | (0.070) | | | (0.086) | | |
| Leverage × lender exposure | | 0.491 | | | 0.402 | | | 0.421 | |
| | | (0.630) | | | (0.669) | | | (0.700) | |
| Maturing LT leverage × lender exposure | | | 2.729 | | | 2.870 | | | 1.577 |
| | | | (2.122) | | | (2.367) | | | (3.770) |
| Remaining LT leverage × lender exposure | | | 0.275 | | | 0.126 | | | 0.109 |
| | | | (0.750) | | | (0.803) | | | (0.870) |
| Lender exposure | -1.042 | -1.174 | -0.984 | -1.088 | -1.170 | -1.017 | -1.066 | -1.237* | -1.123 |
| | (0.689) | (0.727) | (0.778) | (0.695) | (0.729) | (0.781) | (0.690) | (0.735) | (0.789) |
| Liquidity demand × market power | | | | | Yes | | | | |
| Control variables | | | | | Yes | | | | |
| Control variables × lender exposure | | | | | Yes | | | | |
| Firm fixed effects | | | | | Yes | | | | |
| Industry × year-quarter fixed effects | | | | | Yes | | | | |
| Observations | 20,926 | 21,827 | 19,595 | 20,926 | 21,827 | 19,595 | 20,926 | 21,827 | 19,595 |
| R-squared | 0.905 | 0.901 | 0.902 | 0.905 | 0.901 | 0.902 | 0.905 | 0.901 | 0.903 |

## Panel C: ABX exposure

| VARIABLES | *Markup* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Top 3 industry seller × -(z-score) × Exposure | 0.032 | | | | | | | | |
| | (0.046) | | | | | | | | |
| Top 3 industry seller × leverage × Exposure | | 0.831 | | | | | | | |
| | | (0.979) | | | | | | | |
| Top 3 industry seller × maturing LT leverage × Exposure | | | -1.841 | | | | | | |
| | | | (3.541) | | | | | | |
| Top 3 industry seller × Remaining LT leverage × Exposure | | | 1.419 | | | | | | |
| | | | (1.115) | | | | | | |
| Sales/industry sales × -(z-score) × Exposure | | | | 0.444 | | | | | |
| | | | | (0.427) | | | | | |
| Sales/industry sales × leverage × Exposure | | | | | -3.005 | | | | |
| | | | | | (10.285) | | | | |
| Sales/industry sales × maturing LT leverage × Exposure | | | | | | -23.387 | | | |
| | | | | | | (34.961) | | | |
| Sales/industry sales × Remaining LT leverage × Exposure | | | | | | 6.066 | | | |
| | | | | | | (10.986) | | | |
| Herfindahl index × -(z-score) × Exposure | | | | | | | -0.084 | | |
| | | | | | | | (0.424) | | |
| Herfindahl index × leverage × Exposure | | | | | | | | -1.025 | |
| | | | | | | | | (4.716) | |
| Herfindahl index × maturing LT leverage × Exposure | | | | | | | | | 10.061 |
| | | | | | | | | | (23.030) |
| Herfindahl index × Remaining LT leverage × Exposure | | | | | | | | | 4.062 |
| | | | | | | | | | (5.654) |
| -(Z-score) × lender exposure | 0.085*** | | | 0.083*** | | | 0.090*** | | |
| | (0.027) | | | (0.027) | | | (0.034) | | |
| Leverage × lender exposure | | 0.348 | | | 0.355 | | | 0.476 | |
| | | (0.296) | | | (0.317) | | | (0.378) | |
| Maturing LT leverage × lender exposure | | | 1.333 | | | 1.409 | | | 0.758 |
| | | | (1.005) | | | (1.097) | | | (1.711) |
| Remaining LT leverage × lender exposure | | | 0.231 | | | 0.196 | | | 0.187 |
| | | | (0.352) | | | (0.376) | | | (0.474) |
| Lender exposure | -0.883** | -0.933** | -1.061** | -0.893** | -0.935** | -1.068** | -0.873** | -0.933** | -1.103** |
| | (0.403) | (0.403) | (0.434) | (0.405) | (0.403) | (0.436) | (0.401) | (0.404) | (0.437) |
| Liquidity demand × market power | | | | | Yes | | | | |
| Control variables | | | | | Yes | | | | |
| Control variables × lender exposure | | | | | Yes | | | | |
| Firm fixed effects | | | | | Yes | | | | |
| Industry × year-quarter fixed effects | | | | | Yes | | | | |
| Observations | 20,926 | 21,827 | 19,595 | 20,926 | 21,827 | 19,595 | 20,926 | 21,827 | 19,595 |
| R-squared | 0.905 | 0.901 | 0.903 | 0.905 | 0.901 | 0.903 | 0.905 | 0.901 | 0.903 |