Corporate Resiliency and the Choice between Financial and Operational Hedging*

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Abstract

We investigate how firms manage financial default risk (on debt obligations) and operational default risk (on delivery obligations). Financially constrained firms reduce operational hedging through adjustments to inventory and supply chains in favor of cash holdings. Thus, firms' markup increases with financial default risk because they cut operational hedging costs. We show that markup–credit risk relationship strengthens during adverse aggregate shocks, and that markup reacted more strongly to credit risk for firms that became financially constrained when they were shocked in 2008 Financial Crisis. This relationship, reflecting firms' strategic adjustments in operational hedging practices, is unexplained by managerial entrenchment and market power.

KEYWORDS: FINANCIAL DEFAULT, OPERATIONAL DEFAULT, LIQUIDITY, RISK MANAGEMENT, INVENTORY, SUPPLY CHAINS

JEL: G31, G32, G33

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1. Introduction

This paper examines how firms manage the dual risks of financial and operational default. Firms face contractual obligations on two fronts: financial debt contracts and operational contracts to deliver goods and services to customers. When adverse economic shocks occur, firms can face financial default on their debt obligations and operational default on their delivery commitment to customers, as was the case during the COVID pandemic. Given constraints on internal cash flows and limited access to the capital market, firms must optimize their resource allocation to mitigate these two distinct default risks.

Our paper studies the tradeoff that the firm faces between allocating liquid resources to operational hedging, which would strengthen the firm's resiliency, and to the prevention of financial distress. Firms' operational hedging strategies include maintaining excess inventory, diversifying supply chains, and developing backup production capacity.[1] These strategies are costly, yet firms are willing to endure higher production costs to mitigate the risk of failure to deliver on their obligations to customers, which would impair their cash flow and impose a penalty on their reputation and franchise value. The firm's optimal balancing of these two hedging demands—financial hedging and operational hedging—provides a novel explanation for heterogeneity in operational resilience across firms. We find that financially distressed firms reduce operational hedging, particularly when external financing is costly. Because operational hedging raises production costs, cutting such hedging lowers costs and increases the price-cost spread or markup. Thus, for firms with limited access to

[1] Operational hedging became prominent during the COVID pandemic and its aftermath, when corporate operational resilience was challenged by shocks that disrupted supply chains, depleted inventory, and impaired firms' ability to meet their delivery obligations.

external capital, higher credit risk leads to higher markups.[2]

We empirically test whether the firm's markup, (Sales−cost of goods sold)/sales, increases with the firm's credit risk, measured by Altman's Z-score (Altman, 1968, 2013a). A higher negative Z-score (-(*Z-score*)), which indicates greater credit risk, should raise the markup. We control for two measures of market power usually associated with markup, and for other characteristics. The results support our hypothesis. We find that markup increases in -(*Z-score*) with a statistically and economically significant effect: an increase of one standard deviation in the firm's -(*Z-score*) raises the firm's markup by 7% relative to the sample average.[3] Furthermore, higher credit risk significantly lowers the cost of goods sold (CGS) after controlling for the firm's characteristics, consistent with our hypothesis that credit risk affects markup through the lowering of operational hedging costs.

We also test whether financial constraints amplify the positive relationship between markup and credit risk. To do so, we employ macroeconomic financial constraints and exogenous firm-specific shocks to credit supply. First, we find that during NBER-designated recessions, the positive markup–credit risk relationship is significantly stronger and the negative CGS–credit risk relationship is also stronger, suggesting that the positive markup–credit risk relationship is driven at least partly by costs. Firms with higher credit risk also reduced their operational hedging directly during recessions by lowering inventory holdings.[4] Furthermore, we find that firms with high credit risk reduced their leverage during recessions, suggesting

[2]Notably, the effect of credit risk on markup stems primarily from lack of funds to spend on operational hedging, which is an investment in operational resiliency and differs from the debt overhang problem, which lowers investment (Myers, 1977). We elaborate on the difference in Section 2.

[3]Our analysis thus introduces credit risk as a new determinant of the firm's markup, while the market power variables are not found to predict higher markup.

[4]The effect on supply chain hedging is weaker because supply chain relationships involve long-term commitments and take time to adjust, unlike inventory that can adjust quickly.

that they used the cash generated by lowering their operational hedging to reduce their financial risk, consistent with our hypothesis.

Second, we examine whether exogenous firm-specific shocks to credit supply during the 2008 Financial Crisis lead financially constrained firms to exhibit a stronger positive relationship between markup and credit risk. We employ the data of Chodorow-Reich (2014) on banks that were impacted in September 2008 by the collapse of Lehman Brothers and generally by the mortgage-backed securities crisis, which forced them to cut loans. Firms with borrowing relationships with the impacted banks then became financially constrained. We find that for firms that were more exposed to these exogenous credit supply shocks, credit risk had a stronger positive effect on markup and a stronger negative effect on CGS. Notably, we find no difference between the exposed and non-exposed groups during the pre-crisis period. Firms with higher credit risk that became exposed to lenders' shocks also reduced their operational hedging directly by lowering inventory holdings and, to a lesser extent, decreasing supply chain hedging. (See Footnote 4 for a discussion of the slower adjustment speed of supply chain hedging.) Finally, we find that firms with high credit risk whose credit supply was shocked reduced their leverage, suggesting that they employed the cash generated by lowering their operational hedging to lower their financial risk, as we propose. These tests alleviate concerns about the endogeneity of credit risk, as we study here the effect of the pre-crisis credit risk on the post-crisis outcomes for firms that became financially constrained following a shock to their lenders.

We attend to alternative explanations for the positive effect of the firm's credit risk on its markup. The first is based on the disciplining role of debt for inefficient management, following Jensen (1986). By committing firms to payouts, debt forces managers to cut costs during adverse economic conditions. Since cost inefficiencies are more likely among entrenched managers who are shielded from mergers and acquisitions, we rank firms by the entrenchment indices of Bebchuk, Cohen, and Ferrell (2009) and of Gompers, Ishii, and Metrick (2003). We divide firms into groups by whether they are above the median ("High" group) or below the median ("Low" group) of these entrenchment measures and estimate for each group the effects of -(*Z-score*) on markup and CGS in two settings: (i) for firms that became financially constrained in the 2008 Financial Crisis when their lenders were shocked, and (ii) during NBER-designated recessions when external financing is generally constrained. The results show that our proposed effects of -(*Z-score*) on markup and CGS are not stronger for firms with entrenched managers that need disciplining.

The second alternative explanation that we test is based on market power, following Chevalier and Scharfstein (1996) and Gilchrist et al. (2017). These authors propose that firms with market power that become liquidity-constrained can raise their prices and markups and consequently their cash flows. Thus, they can meet their short-term liquidity needs even if it hurts their market share and long-term profitability. Notably, our analyses include variables that control for market power, and our finding of the negative effect of -(*Z-score*) on the CGS supports our proposal that markups of financially constrained firms rise through the lowering of operational hedging costs. Nevertheless, we directly test the market power–based explanation of the positive markup–credit risk relationship by estimating our models separately for firms with high market power—those ranking in the top 15% by share of industry sales each quarter, which are likely to have market power—and the remaining firms. Our findings do not support the market power–based explanation. The positive markup–credit risk relationship is stronger among firms with low rather than high market power. This finding also holds in the contexts of the NBER recessions and the 2008 funding shocks to lending banks. That is, even in times of acute liquidity shortages, the positive markup–credit risk relationship is not associated with higher market power.

A third explanation for our proposed effects of -(*Z-score*) on markup and CGS is due to Maksimovic and Titman (1991). They show that firms may have incentives to lower product quality and marginal cost when they are near financial distress because consumers do not find out about product quality in the short term.[5] This follows the suggestion of Myers (1977) that debt overhang inhibits investments that create value in the long term because existing creditors act like a tax, distorting real investment decisions. Myers' rationale also applies to our case of investment in operational hedging. These are not mutually exclusive cases; managers could lower both product quality and operational hedging in response to the threat of default. We attend to this explanation by testing whether upon financial distress, markups adjust downward in the long term, presumably after most consumers discover that product quality has been lowered. We find no evidence of a significant long-term decline in markup.

Finally, we examine whether avoiding financial default becomes a dominant consideration for firms' valuation. High credit risk may lead to financial default before any operational default such that operational hedging does not help. Testing this prediction using stock returns during the COVID era (2020–2021), we expect that pre-COVID operational hedging choices matter less for the value of firms that entered the COVID era with an already high credit risk. We find supportive results. Investing in operational hedging raises firms' value (by preserving their franchise value) following adverse operational shocks only in firms

[5] Phillips and Sertsios (2013) test this idea in the airline industry and find broadly consistent evidence.

whose credit risk was initially low.

In summary, our novelty is in proposing that firms need to hedge not only against defaults on their financial contracts (their debt obligations) but also against defaults on their operational contracts (their commitment to deliver products to customers). Because both forms of hedging impose demands on the firms' limited resources, financially constrained firms face a tradeoff in allocating those resources to protect against these dual default risks.

1.1 Related Literature

Our paper is related to studies of the real effects of financing frictions that show that these frictions can affect investment decisions and employment.[6] A general theme in these studies is that financial constraints induce firms to focus on short-term actions that boost liquidity, even when they reduce long-term value. For example, Rampini and Viswanathan (2010) argue that constrained firms may be forced to reduce risk management when long-term benefits are high because of short-term financial constraints. The tradeoff between operational and financial hedging that we propose is related to this key idea. Firms reduce value-enhancing operational hedging to save cash and protect themselves against financial distress. Our contribution to this literature is to focus on operational hedging, which had not been examined before, and to quantify the tradeoff between financial and operational hedging. Whereas other studies focus on firms' policies intended to avoid financial default, we propose that firms are subject to two types of costly default that they need to manage: the commonly

[6] See Lemmon and Roberts (2010); Duchin, Ozbas, and Sensoy (2010); Almeida et al. (2012); Giroud and Mueller (2016); see Stein (2003) for a review. There are also studies of the effect of financial constraints and financial distress on financial policies such as cash, credit lines, and risk management; see Almeida, Campello, and Weisbach (2004); Sufi (2009); Bolton, Chen, and Wang (2011); Acharya, Davydenko, and Strebulaev (2012).

analyzed default on financial obligations and our proposed operational default, that is, the failure to fulfill contractual obligations to deliver output to customers.

Our paper also relates to that of Froot, Scharfstein, and Stein (1993), who propose that corporate hedging against cash shortfalls helps the firm mitigate the risk of not being able to finance valuable investment opportunities. Gamba and Triantis (2014) study firms' risk management policies for avoiding financial distress, carried out by holding liquid assets and financial derivatives and by maintaining operational flexibility. In our analysis, operational hedging is not a means to avoid financing shortfalls but, rather, a way to compete with financial hedging. Hedging against cash shortfalls that raise financial default risk reduces the funds available for operational hedging when firms face financial constraints, thus increasing the probability of operational default. In our setting, financial hedging and operational hedging are substitutes.

2. Hypothesis Development

We focus on two types of default risk that compete for firms' limited financial resources: financial default on debt obligations and operational default on customer delivery commitments.

Consider a firm with existing debt obligations and customer contracts that promise the delivery of merchandise. The firm operates in an uncertain environment where economic shocks can threaten both its ability to service debt because of a cash shortage and its capacity to fulfill customer orders because of disruptions to production (e.g., a disruption to its supply chains). Financial default will eliminate shareholder equity, while defaulting on delivery obligations will lower firm value due to a loss in the firm's franchise value (loss of future orders). The firm needs to decide whether it should preserve cash to ensure debt repayment or invest its cash in operational resilience to guarantee customer deliveries.

The answer depends on whether the firm can meet its debt obligations while maintaining operational capabilities. Operational hedging encompasses costly strategies that help firms meet delivery obligations during adverse conditions. These strategies include producing extra output and maintaining it as inventory beyond normal operating needs, diversifying supply chains across multiple suppliers and regions, and investing in backup production capacity. While these investments reduce the risk of operational default, they require significant upfront expenditures that reduce available cash.

Financial default destroys all future value, including both potential revenues from customer contracts and the firm's franchise value. Thus, any investment in operational hedging—no matter how valuable for ensuring customer deliveries—becomes worthless if the firm cannot service its debt. When credit risk is high enough, the threat of financial default takes precedence over operational concerns. Firms cut or eliminate operational hedging to save cash for debt repayment. As credit risk declines, the firm can shift more resources into operational hedging, managing the balance between financial hedging and operational hedging.

The extent of operational hedging is reflected in its cost, which appears directly in the firm's cost structure. Producing extra output for inventory and paying its carrying costs, diversifying supply chains (which entails managing relationships with multiple vendors), and maintaining excess capacity are all reflected in higher costs. These costs flow through to the firm's production cost, reducing profit margins. This logic leads to our first hypothesis.

Hypothesis 1: Firms with higher credit risk exhibit higher markups and lower costs of goods sold.

Notably, the mechanism behind Hypothesis 1 is purely cost-based: by cutting operational hedging, firms lower costs, thus increasing markups even in competitive markets where firms are price takers and output prices are given. Traditional explanations link higher markups under financial distress to firms' ability to raise prices (Gilchrist et al., 2017). In contrast, our mechanism does not require pricing power: even price-taking firms can widen their markups by trimming costly operational hedges when credit risk rises, thereby lowering marginal costs while leaving prices unchanged. We follow this intuition in our empirical work to distinguish our story from the traditional ones.[7]

Our mechanism differs from the debt overhang problem of Myers (1977), which arises from conflicts of interest between shareholders and debtholders. In Myers' framework, shareholders under-invest in positive NPV projects because part of the benefits accrue to creditors. In contrast, our framework involves no such conflict: shareholders reduce operational hedging to preserve cash for debt repayment, a choice that benefits both shareholders (by avoiding equity elimination) and debtholders (by reducing default probability). The reduction in operational hedging reflects resource scarcity and the sequential nature of financial and operational obligations, not a wealth transfer from creditors to shareholders.

2.1 Role of Financial Constraints

The tradeoff between financial and operational hedging is stronger when firms face constraints on external financing. Firms can bridge temporary cash shortfalls by accessing capital

[7]A formal model that supports this intuition is available in the Internet Appendix. We model therein a competitive (price-taking) levered firm's optimal operational hedging policy when facing two types of costly default: financial default (on debt service) and operational default (on customer contracts). We build on the financial hedging framework of Acharya, Davydenko, and Strebulaev (2012) by incorporating operational hedging.

markets or credit lines. They can borrow while pledging their future cash flows from sales. However, when external financing becomes costly or unavailable and the pledgeability of future cash flows is limited, the competition for internal resources between financial and operational hedging becomes more severe. This reasoning leads to our second hypothesis.

Hypothesis 2: The positive relationship between credit risk and markup is stronger for financially constrained firms.

In summary, the core insight is that financial and operational hedging compete for limited firm resources, with financial hedging taking priority when credit risk is high due to the sequential nature of financial and operational obligations. Then, higher credit risk raises markups and lowers costs, effects that intensify when external financing is harder to obtain.

3. Empirical Analysis

We now test the two hypotheses on the link between operational hedging and credit risk. First, greater credit risk or probability of default lowers operational hedging, indicated by an increase in the firm's markup and a reduction in costs of goods sold (CGS). Second, the positive (negative) relationship between markup (CGS) and credit risk is stronger for firms that are financially constrained, as discussed in Section 2.1 regarding firms with lower pledgeability of future cash flows.

We measure operational hedging by $Markup = (Sales - CGS)/Sales$. Increased spending on operational hedging lowers *Markup*. Operational hedging is partly accomplished by hoarding inventory and by broadening supply chains—expanding and diversifying the suppliers with whom the firm works.[8]

We begin by validating that our proposed measures of operational hedging—inventory and supply chain breadth—are consistent with the mechanism underlying our hypotheses by testing whether higher inventory and greater supply chain hedging mitigate the sales decline during economic shocks measured by NBER-designated recessions. Moreover, we test whether markup declines with inventory and supply chain hedging and CGS increases in these two measures of operational hedging.

The firm's credit risk is measured by the negative value of Altman's (1968) Z-score, which increases in the likelihood of default and positively affects the firm's credit spread. Our baseline test, following Hypothesis 1, is whether markup (CGS) is increasing (declining) in credit risk. Second and more importantly, we use financing shocks to test whether tighter financial constraints or lower pledgeability strengthens the positive (negative) relationship between markup (CGS) and credit risk. The first test examines the relationship between -(*Z-score*) and both markup and CGS during NBER recessions, when capital markets are depressed and financing is scarce.

The second test employs the shocks to firms' lenders during the 2008 Financial Crisis, which limited their ability to provide credit to their relationship borrowers, following the analysis by Chodorow-Reich (2014). We test whether the markup and CGS of exposed firms—those whose lenders were more strongly hit by the crisis—exhibited a stronger relationship with their pre-crisis -(*Z-score*). We also test whether the effect of financial distress on markups operates through market power, which enables firms to raise prices. By our proposed

[8]Operational hedging may encompass other measures; inventory and supply chain diversification may, however, be the most salient and easily measured.

mechanism, markup rises in response to greater financial constraints because firms lower their operational hedging costs. We conclude by testing whether greater pre-COVID operational hedging supported firm value during the COVID era (2020–2021) for firms that had lower pre-COVID credit risk.

3.1 Data and Empirical Definitions

We employ quarterly Compustat data from 1971 to April 2020, a span of 197 quarters. We exclude firms in financial industries (SIC codes 6000-6999) and utility industries (SIC codes 4900-4949), and firm-quarters involved in major mergers (Compustat footnote code AB). We include firm-quarter observations with market capitalization of at least \$10 million and quarterly sales of at least \$1 million at the beginning of the quarter, inflation adjusted to the end of 2019. Our sample includes 18,338 firms with an average asset value of \$2.7 billion and a median of \$0.30 billion (inflation adjusted to the end of 2019). Altogether we have 573,041 firm-quarters.

3.1.1 Variable Definitions

Our first dependent variable, *Markup* is defined as sales ($SALEQ$) minus cost of goods sold ($COGSQ$), divided by sales. Our second dependent variable is $CGS/Assets$, defined as the cost of goods sold ($COGSQ$) scaled by total assets (ATQ), which increases with operational hedging costs.

Our key explanatory variable is the firm's credit risk proxied by the negative value of Altman's (1968) Z-score.[9] Das, Hanouna, and Sarin (2009) find that the yield spread on

[9]Since $EBIT$ is not available in Compustat quarterly data, we use $OIBDP$ instead in our calculation

corporate debt is decreasing in the Z-score. The model includes variables that control for the firm's investment and debt capacity: Total assets (in logarithm) accounts for the firm's size; Tobin's Q accounts for the firm's growth prospects, calculated as the sum of the market value of common equity (shares outstanding ($CSHOQ$) 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 (e.g., Covas and Den Haan, 2011). Including Tobin's Q controls for shocks to valuation and growth opportunities that might affect firms with higher credit risk, thus influencing their operational decisions and hedging decisions. Other control variables are cash holdings ($CHEQ$), cash flow ($IBQ + DPQ$), and tangible assets ($PPENTQ$), all scaled by total assets. The models with *CGS/Assets* or *Inventory/Assets* as the dependent variable include the contemporaneous ln *Sales/Assets*, because the CGS and inventory are mechanically related, in part, to current sales shocks. We also control for market power, which affects the firm's markup (Lerner, 1934) and inventory behavior (Amihud and Medenelson, 1989), using a dummy variable that equals one if the firm ranks among the top four sellers in the industry in a given quarter (zero otherwise), and the firm's $Sales/Industry\ sales$. The models include firm fixed effects and industry–quarter fixed effects, using Fama and French's 48 industries, which also controls for changes in the concentration of the industries to which the firms belong.

Operational hedging is indicated by inventory and by supply chain breadth.[10] Inventory scaled by sales (or assets) proxies for output held as buffer stock, in part to hedge against

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of the Z-score (Chen et al., 2017).

[10]The 2020 COVID pandemic highlighted the importance of inventory—which in many cases was impossible to replenish at reasonable cost or in a timely manner—and of supply chain diversification to circumvent shutdowns of some manufacturing facilities.

negative future shocks. The supply chain hedging variable is created using information from the FactSet Revere Supply Chain Relationships database on firms' suppliers, which contains comprehensive relationship-level data between firms, starting from April 2003.[11] The FactSet database notes 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 relationship (e.g., competitor, supplier, customer, partner, etc.), and the firms' geographic origins. We aggregate the relationship-level data to the 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 combinations; (iii) ln(1+number of out-of-region suppliers), that is, not from the firm's region.

We merge the supply chain data with 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 four suppliers from three regions in a given quarter, of which three suppliers are not from the firm's region. The supply chain hedging index, SCH, is the first principal component from the principal component analysis of the three individual measures over the whole panel, which explains 97% of the sample variance. The three measures (i) through (iii) have similar weights of 0.575, 0.580 and 0.578, respectively. A higher value of SCH indicates greater supply chain breadth and more intensive hedging along the supply chain.

Table 1 presents summary statistics of the variables in our study. All continuous variables

[11] FactSet Revere's coverage of supply chain information is much better than Compustat's segment data and used by some supply chain studies (e.g., Ding et al., 2020).

in our analysis are winsorized at 1% and 99%.

[INSERT Table 1.]

3.2 Hedging Operational Risk through Supply Chain and Inventory

Operational hedging encompasses strategies such as building up extra inventory or diversifying supply chains across multiple suppliers and regions. More generally, it reflects spending on slack and excess capacity that enables firms to produce the requisite output in case of operational shocks. While these investments increase costs, they enable firms to deliver on their contractual obligations and maintain higher sales when adverse economic shocks disrupt normal operations.

To validate that our empirical measures capture operational hedging activities, we first test whether firms with higher levels of inventory and supply chain diversification prior to NBER-designated recessions experience smaller declines in sales during the recessions. For each recession period, we estimate a separate cross-sectional regression with the dependent variable being $\Delta(Sales/Assets)$, the change in the average quarterly level of firm sales (scaled by total assets) between the recession quarters and the eight-quarter period before the recession. Because a recession may have warning signs that affect the firms' operational hedging before its onset, we use the inventory and supply chain hedging data ending four quarters before the onset of each recession. The control variables are fixed as of the last quarter before each recession. In these regressions, we exclude firm–quarters with zero inventory.[12] The model includes industry fixed effects, and standard errors are clustered at the industry level.

[12] The results are qualitatively similar when these observations are included.

[INSERT Table 2.]

Table 2 presents the results. Higher levels of inventory and supply chain hedging before the recession mitigate the sales decline in sales during the recession compared with average sales during the eight pre-recession quarters. Naturally, sales declined during recessions,[13] but less so for firms with higher inventory and supply chain hedging before the recession. The coefficients of the pre-recession *Inventory/Sales* are all positive and significant, averaging 0.02 across the six recessions. The *SCH* coefficient is also positive and significant.[14] Overall, we find that firms with higher levels of operational hedging suffer less severe disruptions in output deliveries when recession shocks hit.

3.3 Markup, CGS and Operational Hedging

We test if markup declines when the firm increases spending on operational hedging by regressing *Markup* on inventory and supply chain hedging, our empirical measures of operational hedging, in the following model:

$$\begin{aligned} Markup_{j,t} = \beta_1 * Inventory/Sales_{j,t-1} + \beta_2 * SCH_{j,t-1} + Control\ variables_{j,t-1} \\ + \text{Firm Fixed Effect (FE)} + \text{Industry}*\text{Year–quarter FE} \end{aligned} \quad (3.1)$$

We expect $\beta_1 < 0$ and $\beta_2 < 0$. We also estimate the model with the dependent variable being $CGS/Assets_{j,t}$, expecting $\beta_1 > 0$ and $\beta_2 > 0$.

[13] The average sales-to-assets ratio is 0.012 lower during the recessions than in the pre-recession eight-quarter periods. The average change in the sales-to-assets ratio ranges from −0.023 to 0.007, across the six recessions in our sample. All recessions had an average decline in the sales-to-assets ratio except for the first, 1973Q4–1975Q1.

[14] Data for *SCH* are available only for the recession of 2007Q4–2009Q2.

[INSERT Table 3.]

In Table 3 we find that *Markup* and *CGS* are both affected by the two operational hedging variables. Higher inventory and supply chain hedging significantly lower markup and raise CGS. To illustrate the economic significance of the estimated effects, the estimation in column 1 implies that one-standard-deviation increases in *SCH* and $Inventory/Sales$ lowers markup by 0.01 and 0.04, respectively, while the mean *Markup* is 0.317. After controlling for firms' market power variables and industry–quarter fixed effects (column 2), the estimated effect of *SCH* is 0.007 while the inventory effect remains unchanged. There is no evidence that market power drives up the markup as the coefficients of the two market power variables included in column 2, the *Top 4 industry seller* dummy variable and the firm's $Sales/Industry\ sales$, are 0.0056 and −0.57, respectively, with standard errors of 0.0040 and 0.13. Overall, the results suggest that markup and CGS partly reflect the effects of the firm's operational hedging activities.[15]

3.4 Baseline Results

By *Hypothesis 1*, firms closer to financial distress reduce spending on operational hedging, resulting in higher markups and lower costs of goods sold. We estimate the following model:

$$Y_{j,t} = \beta_1 *\text{-}(\textit{Z-score})_{j,t-1} + Control\ variables_{j,t-1} + \text{Firm FE} + \text{Industry}*\text{Year–quarter FE} \tag{3.2}$$

$Y_{j,t}$ is either $Markup_{j,t}$ or $CGS/Assets_{j,t}$, and -(*Z-score*), which is lagged, increases

[15]These regressions exclude firm–quarters with zero inventory. The results are qualitatively similar when these observations are included.

in the firm's credit risk. By *Hypothesis 1*, -(*Z-score*) has a positive effect on *Markup* and negatively affects *CGS/Assets*. The model includes the control variables used earlier as well as firm and industry–quarter fixed effects, with standard errors clustered by firm and by year–quarter.

[INSERT Table 4.]

Table 4 presents the results. *Markup* is positively affected by the firm's credit risk, measured by -(*Z-score*). A higher likelihood of financial default and a greater need for liquidity to hedge financial risk lead firms to cut spending on operational hedging, lowering unit costs and raising markup for price-taking firms. By the results in column 1 and 2, an increase of one standard deviation in -(*Z-score*) raises the firm's markup by 7% relative to the average markup value, or by 5% after controlling for market power and industry–quarter fixed effects. In columns 3 and 4 we find that the CGS declines in the firm's credit risk. A one standard deviation increase in -(*Z-score*) lowers *CGS/Assets* by 1.5% relative to the average *CGS/Assets*, with a similar effect after controlling for market power variables and industry–quarter fixed effects. Notably, the estimated coefficients of the market power variables do not show that market power raises markups.[16] Our findings are consistent with our prediction that the need to avoid financial default induces firms to shift funds away from operational hedging to support financial resilience.

[16]The coefficient of the *Top 4 industry seller* dummy variable in column 2 is −0.00019 with a standard error 0.0047 (insignificant), while the coefficient of *Sales/Industry sales* is −0.28 with standard error of 0.078 (significant). The negative sign of the coefficient on *Sales/Industry sales* is inconsistent with a price channel interpretation, under which higher market power should raise markup.

3.5 Effect of Financial Constraints

Hypothesis 2 predicts that financial constraints and lower pledgeability of the firm's future cash flows lead to a stronger positive markup–credit risk relationship and a stronger negative CGS–credit risk relationship. Because financial constraints are endogenous, we employ two exogenously imposed shocks to financial constraints: economic recessions and lending cuts during the 2008 Financial Crisis. In the first test we examine the effect of a systematic increase in financial constraints on the relationship between credit risk and both markup and CGS, while in the second test we examine the effect of firm-specific increases in financial constraints on this relationship. By Hypothesis 2, these relations should be strengthened because, when constrained, firms must shift resources from operational hedging to financial hedging.

3.5.1 Recession Periods

Funding liquidity is scarce during recessions, making it harder for firms to raise the capital needed to service their financial obligations. Following *Hypothesis 2*, we test whether credit risk has a stronger effect on markup and costs of goods sold during recessions for financially constrained firms. Our test augments the baseline model of the effect of -(*Z-score*) on markup and CGS in Table 4 by adding an interaction term -(*Z-score*)$\times$*Recession*, where *Recession* is a dummy variable that equals one during the NBER-designated recession quarters and zero otherwise. We also examine the effect of this interaction term on leverage, inventory, and supply chain hedging (SCH) to provide direct evidence on firms' financial and operational hedging responses to recessions. The values of -(*Z-score*) and the firm control variables are fixed throughout each recession at their level in the last quarter before the recession's onset, because they may otherwise be affected by the recession.[17]

The results in Table 5 suggest that during recessions, firms with higher credit risk—a higher -(*Z-score*)—before the recession reduce their operational hedging to a greater extent, reflected in a greater increase in their markup and a greater decline in their CGS. The interaction term -(*Z-score*)×*Recession* has a positive and significant coefficient in the markup regression (column 1) and a negative and significant coefficient in the CGS regression (column 2).

Columns 3 and 4 of Table 5 provide direct evidence on two observable operational hedging activities during recessions. For inventory, the coefficient of -(*Z-score*)×*Recession* is negative and significant (column 3), indicating that firms with higher credit risk reduce their inventory holdings in recessions, consistent with a reduction in operational hedging when becoming financially constrained. For supply chain hedging, we have data for only one recession (during 2007Q4–2009Q2) as opposed to studying six recessions in the inventory model. We find as expected a negative coefficient of -*(Z-score)*×*Recession* (column 4), which is statistically insignificant, perhaps because of the lower power of the test. Also, supply chain relationships involve long-term commitments and take time to unwind, unlike inventory, which can be reduced more quickly.

The negative and significant coefficient of -(*Z-score*)×*Recession* in column 5 implies that firms with higher credit risk reduce their leverage more during recessions. They deployed the cash freed up by cutting operational hedging costs to strengthen their financial resilience,

[17]See, for instance, the recommendation of Roberts and Whited (2013) on the issue of studying the effects of shocks on the dependent variables.

consistent with our hypothesis that financially constrained firms prioritize financial hedging over operational hedging.

Overall, our results support our Hypothesis 2 that, when faced with financial constraints during recessions, firms with higher credit risk shift funds from operational hedging to financial hedging, thus lowering their unit costs and raising their markup.

[INSERT Table 5.]

3.5.2 Credit Supply Shocks in 2008

The second test of the effects of financial constraints on the markup–credit risk relationship employs the firm-specific exposure of firms to the credit shock during the 2008 Financial Crisis when a number of banks could no longer extend credit to firms with which they had lending relationships. We test whether firms whose lenders were adversely affected by the 2008 crisis (exposed firms), exhibit a stronger effect of -(*Z-score*), which is positive for *Markup* and negative for $CGS/Assets$. By Hypothesis 2, firms with higher credit risk that became exposed to shocked lenders—thus becoming financially constrained—should have shifted funds from spending on operational hedging to financial hedging to avoid financial default, thus lowering their costs and raising their markup.

We employ Chodorow-Reich's (2014) three measures of the adverse impact of the 2008 crisis on lenders' ability to provide credit: (i) Percentage of loan reduction, (ii) Lehman exposure, and (iii) ABX exposure.[18] Then, the lenders' exposure is associated with each

[18](i) Percentage of loan reduction is the number of loans that the firm's lenders extended to all firms (excluding the firm in question) in the nine-month period from October 2008 to June 2009, relative to the average of the 18-month period from October 2005 to June 2006 and October 2006 to June 2007; (ii) Lehman exposure, the fraction of a bank's syndication portfolio where Lehman Brothers had a lead role; and (iii) ABX exposure, the extent of banks' exposure to toxic mortgage-backed securities, calculated using the correlation between banks'daily stock returns and the return on the ABX AAA 2006-H1 index.

firms according to its relationship banks.[19] The detailed construction of the three variables at the firm level is provided by Chodorow-Reich (2014), who kindly provided us with the data. We combine the three measures into one lender exposure variable, the first principal component of an analysis done across the sample firms. The weights of the three measures, (i) to (iii), are 0.5939, 0.5627 and 0.5750, respectively, which is close to being equal weights. Our sample here is restricted to the 1,827 firms at the intersection of our main sample and the data of Chodorow-Reich (2014).

Table A.2 in the Appendix presents the pre-crisis average values of the characteristics of firms sorted into two groups, high and low LE, where high LE comprises firms whose first principal component of the three lender-exposure measures falls in the top 25%. We find that firms with higher exposure are larger, possess greater market power, have higher credit risk (higher -(*Z-score*)), and have lower cash holdings. We account for these pre-crisis differences by including the pre-crisis characteristics in our empirical analysis.

We estimate the effect of the exposure to shocked lenders on the markup–credit risk and CGS–credit risk relationships using the following model:

$$
\begin{aligned}
Y_{j,k,t} = \alpha &+ \beta_1 * \text{-}(Z\text{-}score)_{j,2007} \times LE_j \times Post + \beta_2 * LE_j \times Post + \beta_3 * \text{-}(Z\text{-}score)_{j,2007} \times Post \\
&+ \sum_m \beta_{4,m} * Control\ variable_{m,j,t-1} + \sum_m \beta_{5,m} * Control\ variable_{m,j,t-1} \times Post \\
&+ \theta_j + \eta_{k,t} + \epsilon_{j,t}\ .
\end{aligned}
\tag{3.3}
$$

[19]The relationship between our sample firms and bank lenders is calculated using data from the LPC DealScan database. For each firm and each of the three measures, we calculate a weighted average of the measure over all members of the last pre-crisis loan syndicate of the firm, where the weight is the lender's share in that loan syndicate.

$Y_{j,k,t}$ denotes $Markup$, $CGS/Assets$, $Inventory/Assets$, SCH, or $Leverage$ for firm j in industry k in quarter t. LE equals 1 for firms in the top 25% of the combined measure of lender exposure, and -$(Z\text{-}score)_{j,2007}$ is fixed before the crisis at the end of June 2007. The control variables are the same as in the baseline regression (Table 4), fixed at the end of June 2007 for the post-crisis period; the model includes their interaction with the post-crisis indicator. The model includes firm fixed effects and industry–quarter fixed effects, with standard errors clustered at the firm level. The periods studied are the two pre-crisis years, July 2005 to June 2007, and the two post-crisis years, July 2009 to June 2011.[20]

Table 6 presents the results. Consistent with our hypothesis, the coefficient β_1 is positive and significant for markup (column 1) and negative and significant for $CGS/Assets$ (column 2). Markup increased for firms with higher credit risk that became financially constrained if their lenders were adversely affected by the financial crisis. These firms reduced spending on operational hedging, as evident from the significant lowering of $CGS/Assets$, which implies shifting resources from operational hedging to avoid financial default. Gauging the economic significance using column 1, for firms with High LE during the post-crisis period, a one-standard-deviation increase in -(*Z-score*) led to a 0.011 wider markup, constituting about 3% of its average level. Column 2 shows a corresponding decline in $CGS/Assets$ of 0.007, also about 3% of its average.

Columns 3 and 4 of Table 6 examine the impact of exposure to shocked lenders on

[20]The end of the pre-crisis period is set to Q2/2007 because problems in the bank loan market began in Q3/2007. On August 17, 2007, the Federal Reserve took emergency action by cutting the discount rate (the rate at which banks borrow directly from the Fed) to stabilize markets. Banks began tightening credit standards on all categories of loans, including business loans to firms, in 2007Q3—before the NBER-dated recession in 2007Q4—as documented in the 2013 report of the Federal Reserve Bank of Dallas (p. 34 and Table 1). Brunnermeier (2009) also documents that the liquidity crunch at lending institutions began in August 2007.

inventory ($INVT$) and supply chain hedging (SCH). The coefficient β_1 in both regressions is negative and significant, indicating that firms with higher credit risk whose lenders were shocked by the financial crisis reduced their inventory and supply chain hedging. These findings provide direct evidence that firms with high credit risk that became financially constrained scaled back their operational hedging activities.

Column 5 shows that firms used the cash they saved by reducing their operational hedging cost to reduce their leverage, the firm's debt scaled by total assets. The negative and significant coefficient β_1 suggests a greater reduction in leverage by firms with higher credit risk whose lenders were more strongly shocked in the 2008 crisis. These findings directly address the mechanism underlying our main results: financially vulnerable firms exposed to exogenous credit shocks reduce operational hedging, widen their profit margins, and deploy the freed up cash flow to strengthen their financial resilience by reducing leverage. This finding is consistent with our hypothesis: when external financing is constrained, firms with high credit risk prioritize financial hedging over operational hedging, reallocating scarce liquidity resources toward improving their ability to meet debt obligations and avoid financial default.

[INSERT Table 6.]

Finally, we study the dynamic effects of the interaction term -$(\textit{Z-score})_{j,2007} \times LE_j \times Post$ before and after the crisis. We replace the post-crisis indicator $Post$ in equation (3.3) with quarter indicators D_n, so that the triple interaction becomes $\beta_n *$-$(\textit{Z-score})_{j,2007} \times LE_j \times D_n$, where D_n equals one in quarter n and zero otherwise, and n equals $-4, \ldots, -1, +1, \ldots, +4$, $\{+5, +8\}$, with $\{+5, +8\}$ capturing quarters +5 to +8. This numbering applies to the last four quarters in the pre-crisis period, Q3/2006–Q2/2007, the four post-crisis quarters, Q3/2009–Q2/2010, and $D_{\{+5,+8\}} = 1$ applies to quarters Q3/2010–Q2/2011. We expect that the coefficients β_n are insignificant in the pre-crisis period, $n = -4, \ldots, -1$, becoming significant for the post-crisis period, being positive for *Markup* as dependent variable and negative for *CGS* as dependent variable.

Table 7 presents the results. In both columns, the coefficients β_n are mostly significant after the crisis, starting from $n = +1$, while being generally insignificant before the crisis for $n < 0$. At the bottom of each column, we present results of an F-test of the joint significance of all the coefficients β_n in two groups, those before and after the crisis. The F-values show that the coefficients β_n for the post-crisis four quarters are statistically significant while the coefficients for the pre-crisis four quarters are insignificant. Figure 1 presents the point estimates of the β_n coefficients, which show a decline in costs and a rise in markups after the crisis for high-credit-risk firms whose lenders were shocked during the 2008 Financial Crisis—a shock that tightened these firms' financial constraints.

[INSERT Table 7.]

[INSERT Figure 1.]

3.6 Agency Problems and the Markup–Credit Risk Relationship

We examine an alternative explanation: that our findings are driven by financial distress that disciplines managers and mitigates agency problems. Jensen (1986) suggests that debt disciplines managers to be efficient and act in the shareholders' interests by forcing them to make periodic cash payments in servicing the debt. In the same spirit, Ofek (1993) suggests that financial distress may cause managers to aggressively cut costs.

By this analysis, financial distress has a stronger effect on cost cutting in firms where managers' interests are not aligned with those of shareholders, that is, in firms with poor corporate governance and more agency problems, while by our analysis, cutting operational hedging costs and reducing financial distress are consistent with shareholders' interests.

We test these explanations by sorting firms into two groups according to two indexes that indicate more entrenched management and more severe agency problems: Bebchuk, Cohen, and Ferrell's (2009) E-index and Gompers, Ishii, and Metrick's (2003) G-index.

We rank firms by the values of their E-index or G-index using data from the Institutional Shareholder Services governance database and divide them into two groups, above and below the median, where the above-median group is associated with more severe agency problems.[21] We then estimate for each group the effect of the -(*Z-score*) on markup and the CGS. The results are presented in Table A.3. In each panel, columns 1–4 study the effects of the NBER recessions, replicating the analysis in Table 5, and columns 5–8 study the effects of shocks to firm lenders in the 2008 Financial Crisis, replicating the analysis in Table 6. Panel A uses the E-index and Panel B uses the G-index as measures of agency problems.

The results suggest that the disciplining of managers in firms with higher agency costs cannot explain the stronger relationships between -(*Z-score*) and both markup and CGS in times of recessions and the 2008 Financial Crisis. In columns 1–4 of both panels A and B, the coefficients of -(*Z-score*)×*Recession* are insignificant for firms with high E-index or high G-index, which indicate more severe agency problems. Yet, for firms with low values

[21] For the recession analysis, the governance index values are fixed as of the last quarter before the onset of each recession; for the financial crisis analysis, the values in 2006 are used.

of E-index or G-index, the coefficients of -(*Z-score*)×*Recession* are positive and significant for the Markup regressions and negative and significant for the CGS regressions, consistent with a value-maximizing reaction to recession.[22]

For the 2008 Financial Crisis (columns 5–8 of panels A and B), we do not observe that firms with greater agency problems—those with high E or G indexes—raise markups by more. Yet, we find that CGS were significantly cut in firms with lower agency problems—those with lower E or G indexes—which became financially constrained because their lenders were shocked.

Taken together, the results from both the NBER recession setting and the 2008 Financial Crisis setting do not support the agency-based explanation for the effects of -(*Z-score*) on markup and CGS. The effects of -(*Z-score*) on markup and CGS are not stronger in recessions or the 2008 Financial Crisis for firms with high entrenchment indexes, contrary to what an agency mechanism would predict. Rather, the relationship is consistent with optimal policy by value-maximizing firms that trade off financial resilience against operational resilience.

3.7 Market Power and the Markup–Credit Risk Relationship

We test an alternative explanation, due to Chevalier and Scharfstein (1996) and Gilchrist et al. (2017), for the positive markup–credit risk relationship. Under our analysis, which assumes price-taking firms, higher markups during recessions and the 2008 Financial Crisis reflect lower marginal costs due to reduced operational hedging. Chevalier and Scharfstein

[22]Due to data limitations—the E-index and G-index are available starting in 1990—the analysis here includes only two out of the six recessions that are studied in Table 5.

(1996) and Gilchrist et al. (2017) propose that firms with market power that are subject to financial distress may raise their product prices to increase short-term cash flow and thus alleviate their liquidity needs. The cost of doing that is to forgo the benefits of higher market share and long-run profit, which is beneficial if the customer base is sticky. This analysis implies that the positive effect of credit risk and financial constraints on markup is stronger for firms with market power. Naturally, both explanations can play a role: in response to financial distress, firms with market power raise their markup by both raising prices and reducing operational hedging costs, while price-taking firms raise their markup solely by reducing operational hedging costs. The question is whether the positive markup–credit risk relationship, which is stronger when financial constraints increase, is present among competitive firms without market power.

We test the effect of market power on the markup–credit risk relationship by re-estimating our markup models separately for firms with market power—those in the top 15% of all firms in that quarter, ranked by sales as a share of their Fama-French 48 industry's total sales—and for the remaining firms, which can be viewed as price takers. We call these two groups HMP and LMP for high and low market power, respectively. By the models of Chevalier and Scharfstein (1996) and Gilchrist et al. (2017), the positive markup–credit risk relationship should hold for the HMP firms but not for the LMP firms.

We replicate our baseline test of Table 4 on the effect of -(*Z-score*) on *Markup* in Panel A of Table 8. The coefficient on -(*Z-score*) is practically zero for HMP firms but positive and highly significant for LMP firms. That is, the positive effect of credit risk on markup is present among LMP firms but not among HMP firms, suggesting that it is not driven by firms with market power raising product prices.

In Panel B, we replicate the tests of Table 5 on whether markup rises with credit risk during NBER economic recessions. We find that the positive effect of -(*Z-score*) on markup during recessions is highly significant for LMP firms and is not stronger for HMP firms.

In Panel C of Table 8, we replicate the analysis of Table 6, estimating separately for HMP and LMP firms the effect of -(*Z-score*) on markups among firms whose lenders were shocked during the 2008 Financial Crisis, which exacerbated these firm's financial distress. We find no significant difference between HMP and LMP firms in the response of markup to increased financial distress; the response is significant only for LMP firms.

In conclusion, our evidence does not support the proposition that the positive effect of financial distress on markup is due to price increases by firms with high market power. We find this effect among firms with low market power, which we treat as price takers.

[INSERT Table 8.]

3.8 Product Quality and the Markup–Credit Risk Relationship

Maksimovic and Titman (1991) propose that financial distress reduces firms' incentives to maintain their reputation for supplying high-quality products when quality cannot be observed until after the product is purchased. This is because a reduction in quality can lower costs and increase current cash flows at the expense of bondholders who may receive less in the future. The modeling of this corporate policy assumes a finite horizon, which lowers the value of maintaining the long-term reputation of product quality if, in the short term, consumers do not find out. We propose that, in the longer term, when consumers find out about the decline in product quality, demand and prices will decline, thus lowering markup.

Testing this implication, we extend our dynamic analysis in Table 7 by four quarters beyond the original two-year post-crisis window (Q3/2009 to Q2/2011), so that the period now covers three post-crisis years and ends in Q2/2012. If financially distressed firms raised their markups by lowering their product quality and cutting costs, this gain would erod over time, since lower quality is hard to sustain over three years without consumers noticing. Lower product quality reduces demand, prices, and markups. We therefore expect that the rise in markups of financially distressed firms whose lenders were shocked to dissipate as time passes after the 2008 Financial Crisis.

Table A.4 of the Appendix presents estimation results of a model that adds an interaction term for the third year following the 2008 Financial Crisis to the model in Table 7, with quarters $\{+9, +12\}$ covering Q3/2011 through Q2/2012. We find no evidence that the coefficient on -(*Z-score*)$\times LE \times D_n$ declines as the time period gets further from the 2008 Financial Crisis. For example, the t-statistic is insignificant at 0.46 for the difference between the coefficient of this interaction variable in quarters D_{+1} and $D_{\{+9,+12\}}$ (three years after the crisis), and is similarly insignificant at 1.01 for the difference between $D_{\{+5,+8\}}$ and $D_{\{+9,+12\}}$. These results suggest that the increase in markup for firms with higher credit risk whose lenders were shocked was sustained over time. We propose that the higher markup reflects managerial optimization through cost cutting in operational hedging for firms in financial distress, rather than reductions in product quality that would save costs in the short run but could hardly be sustained over time without leading to reputational correction and a subsequent decline in markups. Yet our findings do not necessarily contradict the proposition of Maksimovic and Titman (1991) since the two mechanisms for cost reduction are not mutually exclusive.[23]

[INSERT Table A.4.]

3.9 Operational Hedging and Value Change during the COVID Pandemic

By our analysis, that operational hedging is less relevant for firm value when credit risk is high because for a firm facing higher credit risk, financial default becomes the dominant threat. If the firm defaults on its debt, it might not survive to realize the benefits from its operational hedging. That is, investments in operational resilience become less valuable when the firm's financial survival is at risk.[24] We thus expect that the value-enhancing effects of operational hedging are more likely to be present among firms with lower credit risk, while for firms with high credit risk, operational hedging has little or no effect on firm value because the existential threat of financial default overshadows the consideration of operational benefits.

We test this prediction indirectly using firms' value change following the COVID shock, which created both financial and operational default risks. We expect that the pre-COVID level of operational hedging is beneficial for firms with low credit risk while having no beneficial value effect for firms with high credit risk. Our test estimates a cross-sectional regression of firm stock returns over the years 2020–2021 on the pre-crisis $Inventory/sales$ ratio and *SCH* (supply chain hedging) measured at the end of 2019. The control variables are $Book/market$ ratio and *Size* (both in logarithm), which are known to affect stock returns across firms, at their end-of-2019 values, and the percentage change in sales during

[23]We thank the editor for pointing this out.

[24]This is consistent with Myers' (1977) debt overhang which inhibits investment.

2019 to control for mechanical changes of the $Inventory/sales$ ratio in 2019 due to sale changes. We also include industry fixed effects. Finally, we split our sample into two halves by the sample median of -(*Z-score*) and estimate separate regressions for each group.

The results in Table 9 show that firms with lower pre-COVID credit risk—those with a low -(*Z-score*)—benefited from having had higher inventories and greater supply chain diversification before the crisis. They had higher realized returns, as implied by the positive and significant coefficients for both $Inventory/sales$ and *SCH*. While these coefficients are insignificant for firms with high credit risk, for which operational hedging is less relevant, given the high risk of default. These results are consistent with our theoretical predictions.

[INSERT Table 9.]

4. Conclusion

This paper examines how corporations balance financial resiliency and operational resiliency when facing two types of obligations: financial debt contracts and contracts to deliver a certain amount of goods. Firms manage these risks by allocating liquidity to two forms of hedging: (i) financial hedging through cash reserves to reduce the risk of financial default and (ii) operational hedging through inventory holdings and hedging along supply chains that reduces the risk of operational default such as a failure to deliver on obligations to customers. The tension in this resource allocation is especially pronounced when the firm faces financing constraints, leading to a positive relationship between markup and credit risk.

We present empirical evidence supporting our hypotheses. After showing that markup captures a firm's operational hedging activities, measured by inventory holdings and supply chain hedging, we find that across firms, credit risk raises markup and lowers cost of goods sold (CGS). These relationships are more pronounced when firms face greater incentives to preserve liquidity to avert financial default. Specifically, the positive markup–credit risk relationship and the negative CGS–credit risk relationship are stronger during economic recessions and is more pronounced following the 2008 Financial Crisis for firms whose lenders experienced greater crisis exposure, thus making these firms financially constrained. Overall, our empirical findings strongly support our key hypothesis that the tension between financial and operational hedging becomes more acute when the firm encounters greater external financing constraints.

Future research can develop a more granular understanding of various operational hedging strategies, evaluate their comparative effectiveness, and precisely measure their impact on product prices. Addressing these questions will require more comprehensive data on firms' operational hedging practices.

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Figure 1A: Markup: Coefficient on -(*Z-score*)×*LE*×D_n

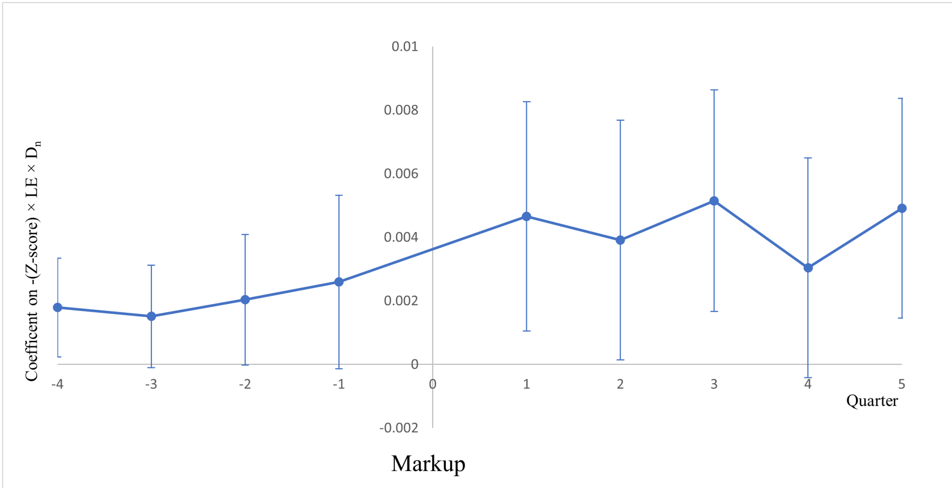

Figure 1B: CGS: Coefficient on -(*Z-score*)×*LE*×D_n

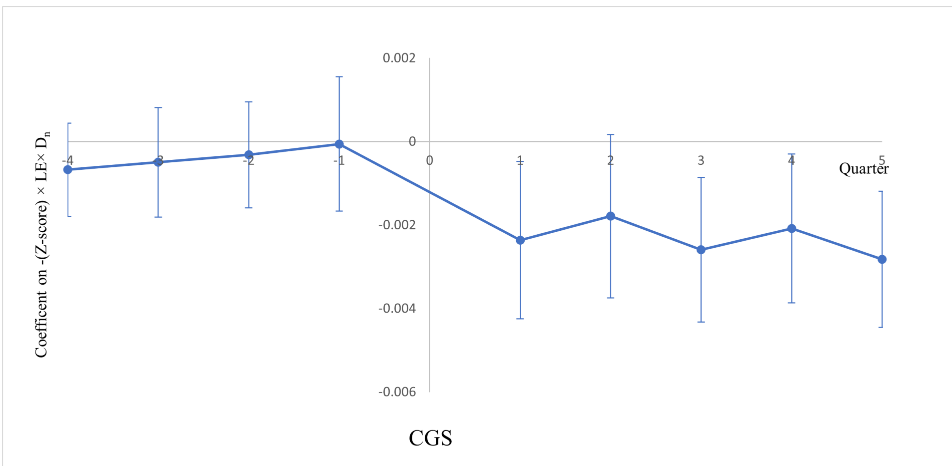

Figure 1: **Markup, CGS and Credit Risk: Dynamic Effects of Exposure to the Financial Crisis**

This figure plots the point estimates from Table 7 of the coefficients on -(*Z-score*)×*LE*×D_n in the *Markup* and *CGS/Assets* regressions, and their 90% confidence intervals. The excluded period, indicated as 0, straddles the 2008 Financial Crisis and covers the period Q3/2007 to Q2/2009. In both panels, "Quarter 5" corresponds to the coefficient on $D_{\{+5,+8\}}$ in Table 7.

Table 1: **Summary Statistics** — Compustat 1971–2020

This table presents summary statistics of the variables in our sample from 1971 to April 2020. The data are quarterly, from Compustat. The variable $Markup$ equals sales ($SALEQ$) minus cost of goods sold ($COGSQ$), divided by sales. The variable *CGS/assets* is CGS($COGSQ$)/total assets(ATQ). Z-score, measuring credit risk, is calculated from quarterly data following Altman (1968). Tobin's Q equals the firm's market value (the sum of common shares outstanding ($CHOQ$) multiplied by the stock price at the close of the fiscal quarter ($PRCCQ$), the preferred stock value ($PSTKQ$), dividends on preferred stock ($DVPQ$), and liabilities (LTQ)), divided by total assets, following Covas and Den Haan (2011). Cash holdings ($CHEQ$), cash flow ($IBQ + DPQ$) and tangible assets ($PPENTQ$) are scaled by total assets. Market power is measured by two variables that employ Fama-French 48 industries: a dummy variable that equals one for the top four industry sellers and zero otherwise; and firm's sales scaled by its industry sales. The operational hedging variables include inventory–sales ratio ($INVTQ/SALEQ$), inventory–assets ratio ($INVTQ/ATQ$), and supply chain hedging index, denoted SCH, composed from a principal component analysis that employs three measures: (i) ln(1+number of suppliers), (ii) ln(1+number of supplier regions), and (iii) ln(1+number of suppliers not from the firm's region). The variable SCH equals 0.575 $\times$ (i) + 0.580 $\times$ (ii) + 0.578 $\times$ (iii). The FactSet data are quarterly, covering $6,204$ firms from mid-2003 to the first quarter of 2020. A firm–quarter is included if 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 1^{st} and 99^{th} percentiles.

VARIABLES	N	Mean	S.D.	P25	P50	P75
$Markup$: (sales-cogs)/sales	572,345	0.32	0.43	0.21	0.34	0.51
CGS/Assets	569,049	0.21	0.19	0.079	0.16	0.28
-(Z-score)	573,041	-3.54	5.87	-4.00	-2.08	-1.08
Tobin's Q	573,041	1.98	1.60	1.07	1.45	2.21
Cash holdings	573,041	0.16	0.20	0.024	0.082	0.23
Cash flow	573,041	0.0097	0.056	0.0052	0.021	0.035
Asset tangibility	573,041	0.30	0.24	0.10	0.24	0.45
Top 4 industry seller	573,041	0.039	0.19	0	0	0
Sales/Industry sales	573,041	0.0089	0.026	0.00018	0.00090	0.0047
Total assets	573,041	2,739	8,391	79.2	299	1,339
Inventory/Assets	557,440	0.14	0.15	0.012	0.100	0.22
Inventory/Sales	563,393	0.49	0.52	0.064	0.38	0.71
Supply chain hedging (SCH)	116,430	-0.010	1.70	-1.33	-0.38	0.96

Table 2: **The Effect of Operational Hedging on Changes in the Sales–Assets Ratio during NBER Recessions**

This table presents the results of cross-sectional regressions of changes in firms' sales–assets ratios during recessions on their operational hedging variables, $Inventory/Sales$ and SCH. The dependent variable is Δ *Sales/Assets*, the difference between average $Sales/Assets$ during the recession quarters and average $Sales/Assets$ over eight quarters before the recession. The recession quarters are as designated by the NBER. *Inventory/Assets* and *SCH* are defined in Table 1; their values are fixed at four quarters before the recession onset (or earlier). All regressions include control variables: Tobin's Q, total assets in logarithm, cash holdings, cash flow, and asset tangibility. All the control variables are fixed as of the last quarter before the onset of each recession. Panel A presents the cross-sectional coefficient on $Inventory/Sales$ for each of the six NBER recessions; Panel B presents the coefficient on SCH for the 2007Q4–2009Q2 recession only. We include Fama-French 48 industry fixed effects, with standard errors (in parentheses) clustered at the industry level. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

VARIABLES	Δ *Sales/Assets*					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Inventory–Sales Ratio						
Recession period	1973Q4 – 1975Q1	1979Q2 – 1980Q2	1981Q2 – 1982Q2	1989Q4 – 1991Q1	2001Q1 – 2001Q3	2007Q4 – 2009Q2
Inventory/Sales	0.037**	0.016**	0.013*	0.016***	0.021***	0.011**
Standard error	0.015	0.008	0.007	0.004	0.004	0.005

Panel B: Supply Chain Hedging, for the Recession of 2007Q4–2009Q2

	SCH
SCH	0.002**
Standard error	0.001

Table 3: **Markup, CGS and Operational Hedging**

Results of regressions of *Markup* (columns 1 and 2) and *CGS/Assets* (columns 3 and 4) on two operational hedging measures: *SCH*, defined as the first principal component of three supply chain diversification measures, and the inventory–sales ratio. All regressions include firm fixed effects and the following controls: Tobin's Q, total assets in logarithm, cash holdings, cash flow, and asset tangibility; year–quarter fixed effects are added in the odd-numbered columns, and two market power variables and Fama-French 48 industry×year–quarter fixed effects are added in the even-numbered columns. The variable definitions are in Table 1. All explanatory variables are lagged by one quarter. The *CGS* regressions (columns 3 and 4) include the contemporaneous $Sales/Assets$ in logarithm. Standard errors (in parentheses) are clustered at the firm and year–quarter levels. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

VARIABLES	*Markup*		*CGS/Assets*	
	(1)	(2)	(3)	(4)
SCH	-0.0076***	-0.0042**	0.0018***	0.0014**
	(0.0021)	(0.0018)	(0.00063)	(0.00065)
Inventory/Sales	-0.076***	-0.076***	0.013***	0.014***
	(0.014)	(0.014)	(0.0022)	(0.0022)
Market power variables	No	Yes	No	Yes
Industry×year–quarter fixed effects	No	Yes	No	Yes
Observations	93,853	92,762	93,772	92,681
R-squared	0.698	0.718	0.934	0.938

Table 4: **Markup, CGS and Credit Risk**

Results of regressions of the quarterly *Markup* (columns 1 and 2) and *CGS/Assets* (columns 3 and 4) on credit risk, measured by Altman's (1968) -(*Z-score*). All regressions include firm fixed effects and the following controls: Tobin's Q, total assets in logarithmic form, cash holdings, cash flow, and tangible assets; year–quarter fixed effects are added in the odd-numbered columns, and two market power variables and Fama-French 48 industry×year–quarter fixed effects are added in the even-numbered columns. All control variables are lagged by one quarter. The variable definitions are in Table 1. The CGS regressions include contemporaneous $Sales/Assets$ in logarithm. Standard errors (in parentheses) are clustered at the firm and year–quarter levels. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

VARIABLES	*Markup*		*CGS/Assets*	
	(1)	(2)	(3)	(4)
-(Z-score)	0.0037***	0.0029***	-0.00053***	-0.00050***
	(0.00057)	(0.00053)	(0.00012)	(0.00012)
Market power variables	No	Yes	No	Yes
Industry×year–quarter fixed effects	No	Yes	No	Yes
Observations	571,388	564,418	568,015	561,177
R-squared	0.614	0.634	0.880	0.885

Table 5: **The Effect of NBER Recessions on Markup, CGS, Inventory, SCH and Leverage**

Results of regressions of *Markup*, *CGS/Assets*, *Inventory/Assets* ($INVT$), supply chain hedging (*SCH*) and *Leverage*, (the ratio of financial debt ($DLTTQ$ plus $DLCQ$) scaled by total assets) on -(*Z-score*) that interacts with a recession dummy variable (*Recession*) equal to one for the following quarters: 1973Q4–1975Q1, 1979Q2–1980Q2, 1981Q2–1982Q2, 1989Q4–1991Q1, 2001Q1–2001Q3, and 2007Q4–2009Q2. For each recession, the values of -(*Z-score*) and the control variables are fixed at their levels in the last quarter before the recession's onset and held constant through the recession. All regressions include lagged control variables (including market power variables), firm fixed effects, and Fama-French 48 industry×year–quarter fixed effects. The CGS and $INVT$ regressions include contemporaneous $Sales/Assets$ in logarithm. Standard errors (in parentheses) are clustered at the firm and year–quarter levels. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

VARIABLES	*Markup*	$CGS/Assets$	$INVT$	SCH	*Leverage*
	(1)	(2)	(3)	(4)	(5)
-(Z-score)×Recession	0.0016***	-0.00031*	-0.00018*	-0.00072	-0.00066**
	(0.00051)	(0.00018)	(0.000090)	(0.0023)	(0.00032)
-(Z-score)	0.0028***	-0.00052***	-0.00018**	0.012***	0.011***
	(0.00052)	(0.00011)	(0.000085)	(0.0020)	(0.00032)
Observations	554,348	551,691	543,331	112,336	538,608
R-squared	0.636	0.886	0.899	0.862	0.720

Table 6: **The Effect of Exposure to the 2008 Financial Crisis on Markup, CGS, Inventory, SCH and Leverage**

This table presents the results of regressions of *Markup*, *CGS/Assets*, *Inventory/Assets* (*INVT*), supply chain hedging (*SCH*), and *Leverage* on -(*Z-score*)×*LE*×*Post*, the interaction of -(*Z-score*) with *LE*, the lender exposure to the 2008 Financial Crisis, and the Post-crisis indicator (*Post*), which equals one for July 2009 to June 2011. The estimated model is (3.3). *LE* is an indicator that equals 1 for firms in the top 25% of the first principal component of the three lender exposure measures from Chodorow-Reich (2014): percentage of loan reduction, Lehman exposure, and ABX exposure. The sample includes 1,827 firms at the intersection of the sample from Chodorow-Reich (2014) and our main sample. The estimation is over two-year periods before and after the crisis, from July 2005 to June 2007 (pre-crisis) and from July 2009 to June 2011 (post-crisis). The firm-level control variables (including market power variables) are as in Table 4, fixed at the end of June 2007 for the post-crisis period. All regressions include control variables and their interactions with the post-crisis indicator, firm fixed effects, and Fama-French 48 industry×year–quarter fixed effects. The *CGS* and *INVT* regressions include the contemporaneous *Sales/Assets* in logarithm. Standard errors (in parentheses) are clustered by firm. ∗, ∗∗, and ∗∗∗ denote significance below the 10%, 5%, and 1% levels, respectively.

VARIABLES	*Markup*	*CGS/Assets*	*INVT*	*SCH*	*Leverage*
	(1)	(2)	(3)	(4)	(5)
-(Z-score)×LE×Post	0.0035**	-0.0023***	-0.0013*	-0.033*	-0.0065**
	(0.0018)	(0.00088)	(0.00074)	(0.018)	(0.0032)
LE×Post	-0.0059	-0.0043	-0.0055*	-0.042	-0.038**
	(0.0078)	(0.0040)	(0.0029)	(0.082)	(0.015)
-(Z-score)×Post	0.0017	-0.00017	0.00042	-0.023*	-0.0081***
	(0.0013)	(0.00068)	(0.00056)	(0.012)	(0.0021)
Observations	19,847	19,847	19,495	13,209	19,441
R-squared	0.921	0.967	0.960	0.919	0.867

Table 7: **Dynamic Effects of Exposure to the 2008 Financial Crisis on Markup and CGS**

This table presents the results of regressions of *Markup* and *CGS/Assets* on -(*Z-score*), interacted with the lender exposure to the 2008 Financial Crisis and quarter indicators around the crisis. The regression specifications, following model (3.3), are the same as in Table 6, except that the Post-crisis indicator is replaced with quarterly indicators D_n, where n equals $-4, -3, -2, -1, +1, +2, +3, +4, \{+5, +8\}$, with $\{+5, +8\}$ capturing quarters +5 to +8. This numbering pertains to the last four quarters in the pre-crisis period, Q3/2006–Q2/2007; the four post-crisis quarters, Q3/2009–Q2/2010; and $D_{\{+5,+8\}} = 1$ for the quarters Q3/2010–Q2/2011. The last two rows show the results from F-tests for the joint significance of the coefficients of -(*Z-score*)×*LE*×D_n. Standard errors (in parentheses) are clustered by firm. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

VARIABLES	*Markup*	*CGS/Assets*
	(1)	(2)
-(Z-score)×LE×D_{-4}	0.0018*	-0.00067
	(0.00095)	(0.00068)
-(Z-score)×LE×D_{-3}	0.0015	-0.00050
	(0.00098)	(0.00080)
-(Z-score)×LE×D_{-2}	0.0020	-0.00032
	(0.0012)	(0.00077)
-(Z-score)×LE×D_{-1}	0.0026	-0.000059
	(0.0017)	(0.00098)
-(Z-score)×LE×D_{+1}	0.0047**	-0.0024**
	(0.0022)	(0.0011)
-(Z-score)×LE×D_{+2}	0.0039*	-0.0018
	(0.0023)	(0.0012)
-(Z-score)×LE×D_{+3}	0.0052**	-0.0026**
	(0.0021)	(0.0011)
-(Z-score)×LE×D_{+4}	0.0030	-0.0021*
	(0.0021)	(0.0011)
-(Z-score)×LE×$D_{\{+5,+8\}}$	0.0049**	-0.0028***
	(0.0021)	(0.00099)
Observations	19,847	19,847
R-squared	0.921	0.967
F-Statistic for post-crisis quarters	2.19*	2.15*
F-Statistic for pre-crisis quarters	1.32	0.30

Table 8: **Markup and Credit Risk: Separate Estimations by Market Power**

In each quarter, firms are sorted by their sales scaled by industry sales into two groups: a high market power (HMP) group, comprising the top 15% of all firms by this measure, and a low market power (LMP) group, comprising the remaining firms. The models are estimated separately for each group. Panel A replicates the test in Table 4: regressions of *Markup* on -(*Z-score*). Panel B replicates the test in Table 5: regressions of *Markup* on -(*Z-score*) that interacts with an indicator of NBER recession periods. Panel C replicates the test in Table 6: regressions of *Markup* on -(*Z-score*) that interacts with the lender exposure to the 2008 Financial Crisis and the Post-crisis indicator. The regression specifications in Panels A, B and C are the same as in Table 4, Table 5 and Table 6, respectively. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

	Panel A: Baseline		Panel B: NBER Recessions		Panel C: Financial Crisis	
	HMP	LMP	HMP	LMP	HMP	LMP
VARIABLES			*Markup*			
	(1)	(2)	(3)	(4)	(5)	(6)
-(Z-score)	0.00064	0.0029***	0.00045	0.0028***		
	(0.00085)	(0.00054)	(0.00086)	(0.00053)		
-(Z-score)×Recession			0.0012*	0.0017***		
			(0.00063)	(0.00053)		
-(Z-score)×LE×Post					0.0027	0.0035*
					(0.0040)	(0.0019)
LE×Post					0.014	-0.0093
					(0.010)	(0.0092)
-(Z-score)×Post					0.0017	0.0016
					(0.0033)	(0.0014)
Observations	78,799	484,875	77,343	476,262	2,781	16,948
R-squared	0.828	0.632	0.820	0.635	0.983	0.913

Table 9: **Operational Hedging and Stock Return during the COVID Period**

Results of cross-sectional regressions of firms' cumulative stock returns over the two-year period 2020–2021 on measures of operational hedging at the end of 2019, ln($Inventory/Sales$) and *SCH*. The control variables are $Book/Market$ ratio, *Size* (equity capitalization), both in logarithm, and the percent changes in sales in 2019. The regressions include Fama-French 48 industry fixed effects. High and low -(*Z-score*) values are those above and below the end-of-2019 sample median, respectively. Standard errors (in parentheses) are clustered by Fama-French 48 industry. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

	2020–2021 stock return		
	Full sample	High -(Z-score)	Low -(Z-score)
	(1)	(2)	(3)
Ln(inventory/sales)	0.015	-0.020	0.051*
	(0.030)	(0.054)	(0.029)
SCH	0.064***	0.021	0.049**
	(0.023)	(0.035)	(0.022)
Ln(B/M)	-0.227***	-0.161	-0.296***
	(0.075)	(0.184)	(0.074)
Ln(size)	-0.135***	-0.171***	-0.052*
	(0.034)	(0.057)	(0.026)
% changes in sales, 2019	-0.190	-0.359	0.132
	(0.218)	(0.354)	(0.254)
Observations	1,664	795	737
R-Squared	0.070	0.096	0.161

Appendix

Table A.1: **Markup, CGS and Credit Risk: Complete Table**

This table reports all the coefficients estimated in Table 4.

VARIABLES	*Markup*		*CGS/Assets*	
	(1)	(2)	(3)	(4)
-(Z-score)	0.0037***	0.0029***	-0.00053***	-0.00050***
	(0.00057)	(0.00053)	(0.00012)	(0.00012)
Tobin's Q	0.021***	0.019***	-0.0023***	-0.0025***
	(0.0020)	(0.0019)	(0.00053)	(0.00052)
Ln assets	0.0073***	0.0058**	-0.0073***	-0.0097***
	(0.0028)	(0.0026)	(0.00092)	(0.00100)
Cash holdings	-0.070***	-0.065***	-0.037***	-0.036***
	(0.015)	(0.015)	(0.0036)	(0.0036)
Cash flow	0.91***	0.85***	-0.17***	-0.16***
	(0.044)	(0.038)	(0.0080)	(0.0076)
Asset tangibility	-0.035**	-0.0061	-0.067***	-0.067***
	(0.014)	(0.014)	(0.0056)	(0.0055)
Top 4 industry seller		-0.00019		-0.0012
		(0.0047)		(0.0039)
Sales/industry sales		-0.28***		0.29***
		(0.078)		(0.040)
Ln Sales/AT			0.14***	0.14***
			(0.0027)	(0.0027)
Market power variables	No	Yes	No	Yes
Industry×Year–quarter fixed effects	No	Yes	No	Yes
Observations	571,388	564,418	568,015	561,177
R-squared	0.614	0.634	0.880	0.885

Table A.2: **Pre-Crisis Firm Characteristics by Crisis Exposure Level**

This table presents firm characteristics before 2008 Financial Crisis across Low and High lender exposure groups (LE) and defined in Table 6. The table reports the mean values for each group and the difference Low minus High, with the corresponding t-statistic in parentheses. $*$, $**$, and $***$ denote statistical significance below the 10%, 5%, and 1% levels, respectively.

Variables	Low LE	High LE	Difference Low minus High
-(Z-score)	-3.461	-2.469	-0.992***
			(-13.200)
Tobin's Q	2.025	2.047	-0.022
			(-0.934)
Asset tangibility	0.284	0.299	-0.015**
			(-2.643)
Ln assets	7.130	7.842	-0.711***
			(-18.496)
Cash holdings	0.107	0.099	0.009**
			(3.132)
Cash flow	0.025	0.024	0.001
			(1.651)
Sales/industry sales	0.013	0.023	-0.010***
			(-11.200)
Top 4 industry sellers	0.055	0.114	-0.059***
			(-8.533)

Table A.3: **Corporate Governance and the Credit Risk Effect on Markup and CGS: Financial Constraints**

This table presents the results of regressions of *Markup* and *CGS/Assets* on interactions of the firm's -(*Z-score*) with a recession dummy variable, *Recession*, and with *LE*, the lender exposure to the 2008 Financial Crisis and the Post-crisis indicator, for firms grouped by corporate governance index levels. In each panel, columns (1)–(4) replicate the analysis in Table 5; columns (5)–(8) replicate the analysis in Table 6. Panel A groups firms by their entrenchment E-index following Bebchuk, Cohen, and Ferrell (2009), and Panel B groups firms by their G-index following Gompers, Ishii, and Metrick (2003). Firms are classified into high and low groups by whether the values of their E or G-index are among the top or bottom 50% of firms, respectively. For the recession analysis, the governance index values are fixed as of the last quarter before the onset of each recession; for the financial crisis analysis, the values in 2006 are used. Other specifications are the same as in Table 5 and Table 6. ∗, ∗∗, and ∗∗∗ denote statistical significance below the 10%, 5%, and 1% levels, respectively.

Panel A: E-Index, Top 50% vs. Bottom 50%

	Panel A: NBER Recessions				Panel B: Financial Crisis			
VARIABLES	*Markup*		*CGS/Assets*		*Markup*		*CGS/Assets*	
	High E	Low E	High E	Low E	High E	Low E	High E	Low E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-(Z-score)×Recession	0.0040	0.0024**	-0.00035	-0.00071***				
	(0.0037)	(0.0012)	(0.00044)	(0.00024)				
-(Z-score)	0.0021	-0.00077	-0.00023	0.00054*				
	(0.0026)	(0.0012)	(0.00043)	(0.00032)				
-(Z-score)×LE×Post					-0.0056	0.0038	0.0028	-0.0018**
					(0.0074)	(0.0026)	(0.0025)	(0.00074)
LE×Post					-0.037**	-0.0050	0.011**	-0.0017
					(0.017)	(0.014)	(0.0051)	(0.0035)
-(Z-score)×Post					-0.00094	0.0024	0.00014	-0.000090
					(0.0025)	(0.0020)	(0.0011)	(0.00050)
					(0.0025)	(0.0020)	(0.0011)	(0.00050)
Observations	38,051	56,699	38,038	56,679	2,399	8,424	2,399	8,423
R-squared	0.765	0.785	0.955	0.953	0.966	0.939	0.996	0.990

Panel B: G-Index, Top 50% vs. Bottom 50%

	Panel A: NBER Recessions				Panel B: Financial Crisis			
VARIABLES	*Markup*		*CGS/Assets*		*Markup*		*CGS/Assets*	
	High G	Low G	High G	Low G	High G	Low G	High G	Low G
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-(Z-score)×Recession	0.0016	0.0023*	-0.00041	-0.00051**				
	(0.0029)	(0.0012)	(0.00041)	(0.00023)				
-(Z-score)	-0.00032	0.0016	-0.00041	0.000067				
	(0.0018)	(0.0015)	(0.00046)	(0.00035)				
-(Z-score)×LE×Post					0.0015	0.0051	-0.0023	-0.0030**
					(0.0024)	(0.0032)	(0.0016)	(0.0013)
LE×Post					-0.043***	0.020	0.0066	-0.011
					(0.015)	(0.018)	(0.0075)	(0.0070)
-(Z-score)×Post					0.0030	0.0011	0.0017	-0.00086
					(0.0025)	(0.0025)	(0.0016)	(0.00079)
Observations	27,838	39,603	27,821	39,587	5,136	6,090	5,136	6,089
R-squared	0.753	0.808	0.956	0.946	0.961	0.932	0.977	0.975

Table A.4: **Dynamic Effects of Exposure to the 2008 Financial Crisis on the Markup Up to Three Years after the Crisis**

This table replicates Table 7, regressing *Markup* on the triple interaction of the firm's -(*Z-score*), its lender exposure to the 2008 Financial Crisis, and quarter indicators around the crisis. Relative to Table 7, we extend the post-crisis period to cover Q3/2011–Q2/2012, captured by the dummy variable $D_{\{+9,+12\}}$. The periods before and after the crisis are July 2005 to June 2007 and July 2009 to June 2012, respectively. The term D_n now includes $n = -1, -2, -3, -4, +1, +2, +3, +4, \{+5, +8\}, \{+9, +12\}$, where $D_{\{+n_1,+n_2\}}$ captures quarters n_1 to n_2 after June 2009. The last two rows show the results from F-tests for joint significance of the coefficients of -(*Z-score*)×*LE*×D_n. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

VARIABLES	*Markup*
	(1)
-(Z-score) × LE ×D_{-4}	0.0019*
	(0.00097)
-(Z-score) × LE ×D_{-3}	0.0015
	(0.00100)
-(Z-score) × LE ×D_{-2}	0.0021*
	(0.0012)
-(Z-score) × LE ×D_{-1}	0.0026
	(0.0017)
-(Z-score) × LE ×D_{+1}	0.0049**
	(0.0023)
-(Z-score) × LE ×D_{+2}	0.0041*
	(0.0024)
-(Z-score) × LE ×D_{+3}	0.0054**
	(0.0022)
-(Z-score) × LE ×D_{+4}	0.0033
	(0.0021)
-(Z-score) × LE ×$D_{\{+5,+8\}}$	0.0051**
	(0.0021)
-(Z-score) × LE ×$D_{\{+9,+12\}}$	0.0037
	(0.0027)
Observations	24,091
R-squared	0.911
F-Statistic for post-crisis quarters	2.10*
F-Statistic for pre-crisis quarters	1.35