The Downstream Channel of Financial Constraints and the Amplification of Aggregate Downturns*

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Abstract

We identify a novel downstream amplification channel through which financial constraints propagate in production networks. Firms experience greater valuation losses during industry downturns when their suppliers are financially constrained, particularly when inputs are more specific and suppliers are more concentrated. Upstream trade credit provision attenuates these effects, consistent with liquidity transmission as the underlying mechanism. Real effects are asymmetric: revenues and costs fall, but investment increases as firms build capital to reduce supplier dependence. Product-level evidence shows revenue declines primarily reflect lower quantities, partly offset by price increases. However, firms with greater inventories sustain production instead of raising prices, indicating inventories buffer upstream credit disruptions. The findings support policies that facilitate trade credit provision in upstream segments and inventory financing in downstream sectors during crises.

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1 Introduction

Financial constraints amplify the severity and duration of adverse shocks, yet some vulnerabilities extend beyond firms' own liquidity management. In modern production networks, the financial soundness of suppliers critically affects customer outcomes (Barrot and Sauvagnat (2016); Kulchania and Thomas (2017)), particularly for firms that rely on supplier trade credit to finance working capital (Garcia-Appendini and Montoriol-Garriga (2013); Almeida et al. (2024)). When suppliers face financial distress, they curtail this credit, with effects cascading downstream. Consequently, financially constrained suppliers may increase customers' exposure to industry downturns, amplifying valuation losses and forcing operational adjustments. Understanding how these vertical amplification effects manifest in investment decisions, production capacity, and pricing strategies, and how they differ from the traditional horizontal amplification channel (Carvalho (2015)), is essential for risk management and crisis policy design.

In this paper, we quantify how upstream financing constraints amplify the effects of industry downturns. To establish the link between downstream economic distress and upstream financing constraints, we leverage advances in production network data developed by Hoberg and Phillips (2010, 2016) and Frésard et al. (2020). Following Almeida et al. (2012) and others, we use corporate long-term debt structure to gauge plausibly exogenous variation in financing constraints. Combining predetermined variation in long-term debt across firms in our production network with the timing of industry downturns, we build on Carvalho's (2015) empirical approach to capture multiple layers of amplification and isolate the contribution of vertical links to firms' exposure to aggregate shocks. The evidence points to a downstream channel in which supply-chain liquidity frictions propagate to customers, with real-side responses following distinctive patterns across sales, costs, and investment. We shed light on operational mechanisms by leveraging retail data that provide product-level sales and prices for consumer goods manufacturers, showing how firms absorb these shocks through adjustments in both quantities and prices, with inventories playing a moderating role in these responses.

The baseline results demonstrate that firms suffer significantly larger valuation losses during industry downturns when their suppliers face higher shares of long-term debt maturing. Controlling for direct and horizontal amplification effects (Carvalho (2015); Garcia-Appendini (2018)), our preferred specifications show that firms with above-median supplier financial constraints experience lower quarterly abnormal returns of 1.08–1.42 percentage points during industry contractions. These estimates are economically significant, corresponding to an amplification of 11% to 17% of downturn effects over the sample period (1996–2019).

A cross-sectional heterogeneity analysis of firms and suppliers reveals the conditions and underlying mechanisms driving these amplification effects. First, the results show that the baseline amplification effects are monotonic in the severity of downturns and suppliers' level of financial constraints, validating our empirical approach. Consistent with our identification strategy, the results also show that the adverse impacts of industry downturns are more pronounced when a firm's constrained suppliers rely significantly more on long-term debt.[1] Importantly, the baseline effects are attenuated when trade credit provision is high, as measured by downstream firms' accounts payable or constrained upstream firms' accounts receivable. This finding is consistent with trade credit being the channel through which financing constraints increase downstream firms' exposure to shocks. Simply put, lower cash flows combined with reduced capacity to tap suppliers for liquidity during downturns undermine a firm's ability to meet its operational expenses, further eroding its value.

The results are stronger when firms rely on specific inputs, as proxied by constrained suppliers' R&D expenditures, consistent with Barrot and Sauvagnat's (2016) argument that input specificity is crucial for the downstream propagation of shocks. This finding also aligns with Custódio et al. (2023), who show that clients substitute away from financially distressed suppliers when switching costs are low. To investigate further, we also proxy for dependence on suppliers with a firm-level measure of upstream concentration, under the premise that it is harder to switch among highly concentrated suppliers. Moreover, this measure may also capture input specificity to some extent, as only larger suppliers can provide specific inputs when suppliers differ sharply in size. Accordingly, the results show that the amplification effects are positively related to upstream concentration. These results suggest that the cost of switching suppliers is key to downstream amplification, whereby constrained suppliers have fewer incentives to extend credit to customers with worse outside options, forcing customers to operate with lower liquidity during downturns.

[1] This is consistent with the premise that even if a firm has a significant *proportion* of debt maturing, it is less likely to be a binding constraint on the firm's liquidity if its *level* of long-term debt is negligible.

To uncover the operational factors driving our valuation results, we examine real effects on both firms' balance sheets and product-level outcomes. The channels through which different amplification effects manifest are distinct: while horizontal amplification primarily affects firms' investment capacity and asset value (Carvalho (2015)), downstream amplification should reflect supply chain disruptions, hampering production capacity and, ultimately, affecting pricing policies. Balance sheet analysis confirms that firms with constrained suppliers experience reduced sales and costs during downturns, consistent with lower production capacity. Notably, the results show evidence of *increased* investment, suggesting that firms build capital to reduce long-term reliance on constrained suppliers. These nuanced results reveal that downstream amplification affects firms' balance sheets asymmetrically, with detrimental effects specifically on production-related measures, reinforcing its distinct supply chain nature.

To shed further light on these production effects, we leverage product-level data from NielsenIQ Retail Scanner, allowing us to decompose revenues into prices and quantities for a subsample of consumer goods manufacturers. The results show that revenue declines are driven primarily by sharp reductions in quantities sold, with firms partially offsetting these losses through price increases. Motivated by evidence that credit-constrained firms cut prices to liquidate inventories and generate short-term cash flows (Kim (2020); Lenzu et al. (2024)), we also show that these effects are significantly attenuated among firms with higher inventories before downturns. These findings imply that inventories act as a buffer against supplier credit constraints, allowing firms to maintain production levels rather than absorbing shocks through higher prices.

An accurate measurement of firm-to-firm relationships is critical for production network analysis. Our main exercise uses the Text-based Network Industry Classifications (TNIC) and the Vertical Textual Network Industry Relatedness Classification (VTNIC) developed by Hoberg and Phillips (2010, 2016) and Frésard et al. (2020), respectively. These datasets build on textual analysis of 10-K filings to identify firm-specific, time-varying potential peers and suppliers, thereby improving the accuracy of fixed industry classifications such as SIC, NAICS, and Input-Output (IO) matrices. In particular, they allow us to construct variables relative to both suppliers and industry peers at the *firm* level, improving the precision of the estimates. However, it is important to stress that the VTNIC measures *potential* vertical relatedness—the likelihood that two firms operate in vertically related product markets—rather than actual transaction flows between firm pairs.[2] Therefore, at a minimum, our results show that industry downturns are exacerbated when upstream industries are financially constrained.[3] Despite this caveat, we show that our framework captures both direct and horizontal amplification effects of financing constraints previously documented by Almeida et al. (2012) and Carvalho (2015). In addition to validating the data and our empirical approach, this allows us to put our results into context and consolidate findings on amplification effects.

Our measure of financial constraints builds on an extensive literature in empirical corporate finance. Following Almeida et al. (2012) and others, we use a firm's *ex-ante* annual debt-maturity structure to construct an exogenous measure of the availability of funds.[4] As maturing debt must be either paid or rolled over, firms with large shares of long-term debt due at a given moment have less discretionary liquidity. The primary concern with this approach is that corporate debt structure is endogenously determined, raising questions about the causal interpretation of the results. In particular, variation in long-term debt maturity across firms might reflect unobservable factors that correlate with the incidence of downturns, such as managerial ability. Our empirical design mitigates these concerns by exploiting variation in debt maturity across suppliers, which is plausibly exogenous to the timing of their customers' industry downturns.

We establish the robustness of our results in several ways. To ensure that our tests do not capture unobservable confounders, we include firm fixed effects to control for any time-invariant firm-level characteristics, including persistence in suppliers' debt maturity levels and any systematic tendency for firms with constrained suppliers to suffer more frequent or deeper downturns. Following Carvalho (2015), we also include downturn–quarter fixed effects and interactions of the downturn indicators with all control variables. This means that the identification of effects comes from cross-sectional variation in suppliers' debt maturity *within downturns in the same quarter*, while also accounting for differential sensitivity to downturns stemming from firms' observable time-varying characteristics, such as tangibility and size (Almeida and Campello (2007); Hadlock and Pierce (2010)). Consequently, our estimates

[2]Nevertheless, we use "upstream firms" and "suppliers" interchangeably for an easier exposition.

[3]For completeness and robustness purposes, in Appendix A.2 we replicate our main results in an auxiliary exercise that employs the traditional fixed industry classifications commonly used in the literature. We connect industries vertically using benchmark IO tables published by the Bureau of Economic Analysis (BEA), following a procedure similar to that of Becker and Thomas (2011) and Almeida et al. (2017, 2019). We confirm our main findings under these specifications, addressing concerns that our results rely on fluid industry definitions and potential vertical-relatedness.

[4]See, e.g., Carvalho (2015); Benmelech et al. (2019); Granja and Moreira (2022); Oliveira et al. (2024).

capture the *additional* impact of having constrained suppliers during downturns, comparing firms that experience aggregate shocks at the same time but differ in upstream financial constraints, beyond any systematic relationship between supplier constraints and a firm's overall exposure to negative shocks.

Finally, in a robustness exercise, we address the concern that firms adjust their debt maturity horizons in anticipation of downturns by predicting firms' financial constraints using debt maturity levels computed three years in advance (cf. Duchin et al. (2010); Almeida et al. (2012); Carvalho (2015)). In our framework, endogeneity in these tests would imply that managers have at least three years of foresight into downturns in downstream industries and adjust their long-term debt maturity accordingly. We show that our main results hold under this specification, albeit with slightly smaller magnitudes, reflecting increased measurement error in our proxy for suppliers' financing constraints.

A rich body of work examines how firms are influenced by their peers, their financial environment, and their production network.[5] Barrot and Sauvagnat (2016) document that firms experience output losses when natural disasters hit their suppliers. Gao (2021) shows that firms centrally connected in production networks tend to hold more cash, thereby attenuating the propagation of shocks. Grieser et al. (2025) document how financial constraints trigger network effects in investment decisions. Other studies assess how firms benefit from supply chain interactions via trade credit as a form of liquidity provision (Garcia-Appendini and Montoriol-Garriga (2013); Gofman and Wu (2022); Giannetti (2024)). Conversely, Costello (2020) shows that liquidity shocks propagate downstream via lower credit and sales, while Altinoglu (2021) argues that trade credit linkages can propagate financial shocks upstream, amplifying aggregate fluctuations. Finally, Custódio et al. (2023) and Ersahin et al. (2024) provide evidence of indirect economic costs of financial distress arising from customers substituting away from constrained suppliers, emphasizing the role of trade credit in promoting supply chain stability.

Our paper contributes to the literature in multiple ways. First, prior studies focus primarily on pure *contagion* effects through firm networks. In contrast, we document that financial constraints also propagate downstream through *amplification* effects arising from disruptions to trade credit. In addition, we show that valuation losses are accompanied by distinct balance-sheet effects, with lower costs and sales but *higher* levels of investment. Collectively, our findings are consistent with production

[5]On product markets and financial constraints, see, e.g., Frésard (2010); Lemmon and Roberts (2010); Carvalho (2014); Carvalho et al. (2015); Bustamante and Donangelo (2017); Bustamante and Frésard (2021). On production networks, see, e.g., Petersen and Rajan (1997); Brown et al. (2009); Cortes et al. (2019); Gofman et al. (2020); Grigoris and Segal (2024).

disruptions in which firms build capital to reduce reliance on constrained suppliers. Finally, using product-level data for consumer goods manufacturers, we document that these valuation and balance-sheet effects ultimately reflect production capacity and pricing policies.

Our paper also relates to an extensive literature on how financial constraints affect firms' real and financial policies (e.g., Fazzari et al. (1988); Campello et al. (2010); Fee et al. (2009); Campello et al. (2011)). In a seminal paper, Opler and Titman (1994) find that highly leveraged firms lose market share to industry peers during downturns. Almeida et al. (2012) document that firms with a high fraction of long-term debt maturing during the Global Financial Crisis cut investment significantly more than otherwise similar firms. Carvalho (2015) and Garcia-Appendini (2018) show that financing constraints amplify negative shocks within industries. More recently, Almeida et al. (2024) show that financing frictions hinder investment in working capital, reducing production capacity and propagating operating losses over time, especially in firms that rely on supplier financing. We contribute by uncovering a distinct layer of amplification effects and highlighting the importance of inventories in firms' cash flow management during downturns, allowing them to maintain sales levels and pricing policies.

Lastly, our paper contributes to a burgeoning literature on financing constraints and pricing strategies, made possible largely by the availability of granular data on product-level sales and prices, such as NielsenIQ Retail Scanner. Kim (2020) and Lenzu et al. (2024) show that credit-constrained firms engage in "fire sales" by cutting prices to liquidate inventories and generate short-term cash flows. Investigating corporate bankruptcy among consumer goods manufacturers, Campello et al. (2025) condition the fire-sale behavior on liquidating firms only, while firms that emerge from bankruptcy keep prices on par with competitors. Our paper reveals *supplier-driven* pricing effects of financial constraints, in which upstream credit disruptions reduce firms' production capacity. In addition, we show that price responses to distress are primarily determined by existing inventories, whereby firms with low inventories increase prices to compensate for lost production rather than engaging in fire sales.

2 Empirical Strategy

2.1 Data, Sample Construction, and Summary Statistics

We use data on U.S. firms from Compustat North America Fundamentals Annual and Quarterly. Stock prices and returns are from the Center for Research in Security Prices (CRSP). Our baseline sample covers the years 1996-2019. The data construction and filters closely follow standard practice in the literature. First, we exclude financial institutions (SIC codes 6000–6999) and regulated utilities (SIC codes 4900–4999). We remove firm-quarter observations with missing or negative values of total assets (`atq`), cash holdings (`cheq`), capital expenditures (`capxy`), total revenue (`revtq`), and property, plant, and equipment (`ppentq`). Variables measured in dollars are deflated to 2012 values using the quarterly GDP deflator from the Federal Reserve Bank of St. Louis' FRED database.

Outcome Variables. Our main outcome of interest is *Abnormal Return*, a firm's quarterly stock return minus the return of a benchmark portfolio of stocks matched on size, book-to-market, and previous quarter returns, as in Daniel et al. (1997). To examine the real effects of downstream amplification, we construct four balance-sheet dependent variables.

The first two relate to tangible investments and assets and follow closely those in Carvalho (2015). *Investment Change* is the difference in *Investment* between the current and previous year, where *Investment* is the ratio of quarterly capital expenditures (`capxy`) to the quarterly lag of property, plant, and equipment (`ppentq`). Similarly, *Change in Asset Sale* is the difference in *Asset Sale* between the current and previous year, where *Asset Sale* is the ratio of quarterly sale of property (`sppey`) to the lag of property, plant, and equipment.[6] To assess disruptions in production and supply chains, we construct two analogous variables related to sales and costs. *Change in Sales by Assets* is the annual change in *Sales by Assets*—the ratio of sales (`saleq`) to the lag of total assets (`atq`). Similarly, *Change in Costs by Assets* is the annual change in *Costs by Assets*—the ratio of costs of goods sold (`cogsq`) to lagged assets. All outcome variables are measured in percentage points and winsorized at the 1% tails.

[6]Variables `capxy` and `sppey` represent "year-to-date" values, which we adjust to reflect quarterly values.

Firm Controls. We construct firm-level quarterly control variables as follows. Q is the ratio of total assets plus market capitalization minus common equity minus deferred taxes and investment credit (`atq + prccq` $\times$ `cshoq - ceqq - txditcq`) to total assets. *Cash Flow* is the ratio of operating income before depreciation (`oibdpq`) to lagged assets. *Cash* is cash and short-term investments (`cheq`) divided by total assets. *Size* is the natural logarithm of total assets. *Rated* is an indicator that equals one if a firm's S&P long term issuer credit rating (`splticrm`) is non-missing, and *Investment Grade* is an indicator of `splticrm` being between AAA and BBB. *Leverage* is total debt (`dlttq + dlcq`) divided by total assets, and *Tangibility* is property, plant, and equipment scaled by total assets. All ratios are winsorized at the 1% tails.

Industry Controls. We define several industry variables to control for product market characteristics in our specifications. However, the definition of a firm's industry depends on the data we use to gauge horizontal relatedness. In our main exercise, we use the Text-based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2010, 2016). The authors construct firm pairwise similarity scores based on text analysis of product descriptions from firms' 10-Ks, filed yearly with the Securities and Exchange Commission (SEC).

Intuitively, these scores measure the similarity between the product descriptions of two firms. When this value is above a certain threshold, firms are classified as peers and enter the database. TNIC industries improve on traditional fixed industry classifications such as the Standard Industrial Classification (SIC) and the North American Industry Classification System (NAICS) for two main reasons. First, if a firm's product descriptions significantly change, its industry peers are updated accordingly, providing more flexibility over time. Second, TNIC industries are not transitive: each firm has its own distinct set of peers, allowing industry variables to be defined at the firm level rather than forcing all firms into predetermined categories. To construct our firm-level industry controls, we use the TNIC-3 database, which is conceptually as coarse as 3-digit SIC codes.[7]

Industry controls are defined as follows. *Industry Leverage* is the average value of *Leverage* across peers. HHI^{ind} is a Herfindahl–Hirschman index based on industry revenues. *Industry Asset Maturity* is the average value of *Asset Maturity*, which is an annualized weighted average of property, plant, and

[7] The pairwise similarity score threshold is calibrated so that the likelihood of two random Compustat firms being in the same industry is 2.05%, as in the 3-digit SIC classification (Hoberg and Phillips (2010)).

equipment maturity (`ppegtq`) scaled by depreciation (`dpq`), and current assets maturity (`actq`) scaled by the cost of goods sold. Finally, *Industry Revenue Growth* is the industry median of the log difference between current and lagged total revenue (`revtq`).

Measuring Vertical Relatedness. In our main exercise, we measure supply chain connections using Frésard, Hoberg, and Phillips's (2020) Vertical Textual Network Industry Relatedness Classification (VTNIC). This classification is based on 10-K product descriptions and the Bureau of Economic Analysis (BEA) Input-Output (IO) tables to link firms vertically. Intuitively, if a firm's product description matches another firm's input description, then the former is considered potentially upstream relative to the latter. For each firm and year, the database identifies a group of potential suppliers based on pairwise directed vertical relatedness scores, whereby the vertical score for firms i, j measures the degree to which firm i is upstream relative to firm j. Although the measure is based on product descriptions rather than actual data on transactions between firms—thus measuring the *potential* degree of vertical relatedness—Frésard et al.'s (2020) thoroughly validate their database by performing multiple tests. Specifically, they show that their method reasonably captures actual supplier-customer relationships reported in other network databases, and that the provision of trade credit by upstream firms is positively correlated to the use of trade credit by downstream firms.

Following Frésard et al. (2020), we use the 10% granularity database, which includes pairs of firms with vertical score in the top 10% of all pairwise scores in a given year.[8] As with TNIC (horizontal) industries, a key innovation of this vertical classification is that each firm has its own set of potential suppliers each year, allowing us to define variables relative to suppliers at the firm level. As detailed in Section 2.2, we use the VTNIC to construct our measures of firms' suppliers' financial constraints.

Finally, in a robustness exercise, we use the Bureau of Economic Analysis's IO tables to identify pairwise vertical relationships among industries. We use the benchmark IO tables that provide data at the most granular BEA industry classification ("Detail"), which can be matched to NAICS industries.[9] Tables at this level are released every five years, and we use the publications from 1997 to 2017. As in

[8] Frésard et al.'s (2020) data library also includes full-network data. They nonetheless argue that the 10% granularity is appropriate for most purposes, as vertical-relatedness below the 90% quantile is negligible.

[9] Most Detail-level industries correspond to 5- and 6-digit NAICS.

Becker and Thomas (2011) and Almeida et al. (2017, 2019), we use these matrices to build industry-level variables relative to supplier industries, as we describe in detail in Appendix A.2.

Summary Statistics. Table 1 reports summary statistics for the sample used in our main exercise. It covers 274,313 firm-quarter observations from 1996 to 2019. Panel A reports firm variables, and Panel B reports TNIC-3 industry firm-level variables. Our summary statistics are consistent with previous studies (see, e.g., Carvalho (2015)). For example, in the sample used in our main exercise, the mean and median *Abnormal Return* are –0.2% and –2.3%, respectively, implying a positively skewed distribution.[10]

— PLACE TABLE 1 ABOUT HERE —

2.2 Measuring Financial Constraints

Following Almeida et al. (2012) and others, we use the *ex-ante* maturity structure of long-term debt to predict firms' financial position in a given year. The reasoning is that firms with high proportions of long-term debt due are short on internal funding sources, as they must meet their debt payments or roll them over, which is particularly binding during downturns. Thus, we exploit cross-sectional variation in firms' *ex-ante* debt maturity to build our firm financing constraint measure. This empirical design requires sufficient heterogeneity in firms' long-term debt maturity. Several frictions prevent firms from uniformly distributing maturity over time, as Almeida et al. (2012) document. Additionally, Carvalho (2015) shows that cross-firm variation is sufficient to identify industry-level financial constraints when aggregated at the 3-digit SIC code level.

Although our final sample is a quarterly panel, corporate debt maturity variables are only available for most Compustat firms at an annual frequency. The variables `dd1` and `dltt` report the dollar value of long-term debt due in one year and in more than one year, respectively. Hence, the one-year lag of the ratio of `dd1` to (`dd1 + dltt`) is a firm's fraction of long-term debt due in a given year as predicted in the previous year.

Firm-Level Indicator of Financial Constraints (FC^f). Following Carvalho (2015), a firm is considered *financially constrained* when its fraction of long-term debt due is in a sufficiently high quantile of its

[10]The 1%-level winsorization of *Abnormal Return* variable explains its non-zero mean.

yearly distribution. Our firm-level financial constraint variable is FC^f, an indicator variable equal to 1 if a firm is in the top tercile of this distribution. This quantile approach ensures sufficient variation in financing constraints across firms within years and controls for secular trends in aggregate debt maturity (Custodio et al. (2013)). It still captures significant cross-sectional differences in debt maturity: firms classified as financially constrained have, on average, 39.7% of long-term debt due, whereas this figure is only 10.4% for unconstrained firms. Next, we describe how we use our firm-level financing constraint variable to construct industry and supplier constraint variables in our main exercise.

Firm-Level Indicator of Industry Peers' Financial Constraints ($\mathbf{FC^{ind}}$). In our main exercise, we use FC^f and TNIC-3 industries to build our industry financial constraint indicator. For firm i and quarter t, we compute:

$$FC^{ind}_{i,t} = \frac{\sum\limits_{k \in I(i,t)} FC^f_{k,t}}{\#I(i,t)},$$

where $I(i,t)$ is the set of firm i's industry peers in quarter t, and $\#I(i,t)$ is the number of firms in the set. Hence, FC^{ind} is the share of firm i's peers that are financially constrained, as measured by FC^f. Following Carvalho (2015), we construct an indicator variable FC^{ind}_{50} that equals one if FC^{ind} is in the top 50% of its yearly distribution, and zero otherwise.

Firm-Level Indicator of Suppliers' Financial Constraints ($\mathbf{FC^{sup}}$). We use FC^f and VTNIC networks to build the firm-level suppliers' financial constraint indicator used in our main exercise. Analogously to $FC^{ind}_{i,t}$, for firm i and quarter t, we compute:

$$FC^{sup}_{i,t} = \frac{\sum\limits_{k \in S(i,t)} FC^f_{k,t}}{\#S(i,t)},$$

where $S(i,t)$ is the set of firm i's upstream firms in quarter t, and $\#S(i,t)$ is defined accordingly. We construct an indicator variable FC^{sup}_{50} that equals one if $FC^{sup}_{i,t}$ is in the top 50% of its yearly distribution, and zero otherwise. Firms in the top and bottom 50% of this distribution have, on average, 37.7% and 15.7% of their suppliers classified as constrained, respectively. We also define FC^{sup}_{33}, an indicator that equals one if FC^{sup} is in the top tercile of its yearly distribution, zero if in the bottom tercile, and is missing otherwise. We use these two variables to capture the sensitivity of amplification effects to different degrees of financial distress across suppliers.

A major advantage of using indicator variables is that they address measurement errors in financial constraints. Indicator variables capture the discontinuous effects of debt maturity more accurately than assuming linear relationships across all levels of debt maturity, particularly when liquidity constraints bind. Thus, marginal increases in the fraction of long-term debt due in a year or in the fraction of high debt maturity suppliers may fail to capture tail phenomena.[11]

Horizontal and Vertical Industry Correlations. One concern about using financing constraint indicators for both firms' industry peers and suppliers is the extent to which these two groups overlap. Specifically, if a firm's supplier is also highly likely to be considered an industry peer, the correlation between FC^{ind} and FC^{sup} could be sufficiently high to blur the distinction between horizontal and vertical amplification effects. However, Frésard et al. (2020) find that horizontal contamination in the VTNIC data is low. The authors report that 1.52% of firm-pairs in the VTNIC (10% granularity) also appear as TNIC-3 peers, and 7.17% of firm-pairs in the TNIC-3 networks also appear in the VTNIC database. In our sample, these numbers are 1.69% and 11.72%, respectively. Furthermore, the correlation of FC_{50}^{ind} with FC_{50}^{sup} and FC_{33}^{sup} is –0.036 and –0.054, respectively, suggesting that horizontal and vertical overlap is not a threat to the validity of our results.

2.3 Measuring Industry Downturns

To identify periods of industry economic distress, we follow Carvalho (2015) and Opler and Titman (1994). In each quarter, we require firms' peers to experience a negative median stock return and an abnormally low median revenue growth. We use different thresholds of the overall distribution of firms' industry median revenue growth to construct downturn indicators of varying severity. The variables D_1^{ind}, D_2^{ind}, and D_3^{ind} are indicators that a firm's industry peers experienced both negative median stock returns and median revenue growth in the bottom 20%, 33%, and 50% of its overall distribution, respectively, therefore representing downturns of decreasing severity.

[11] In the Appendix, we show that our main results are robust to using continuous measures.

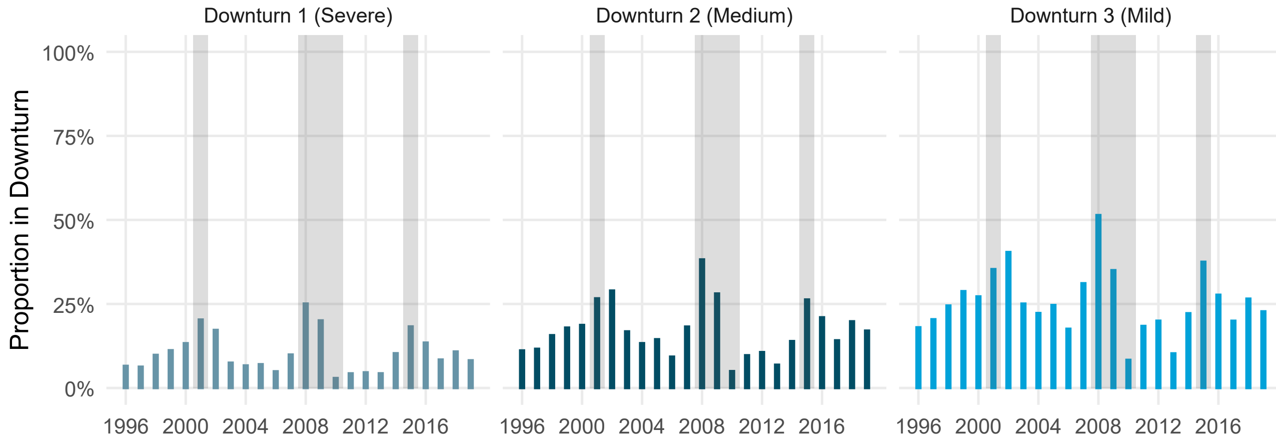

Figure 1. Time Series of Industry Downturns by Severity (1996–2019). This figure plots the annual time series of the proportion of firm-quarter observations experiencing an industry downturn according to indicator variables D_1^{ind}, D_2^{ind}, and D_3^{ind}. These variables indicate if a firm's industry peers experienced both negative median stock returns and median revenue growth at the bottom 20%, 33% and 50% of its overall distribution, respectively. Shaded areas denote NBER recession dates, except for the last one in 2015, which marks the commodity price bust.

To address concerns that industries' debt structure might predict economic distress, we define industry downturns using a broader definition of industry (Carvalho (2015)). In our main exercise, we construct industry financial constraint indicators and control variables using TNIC-3 industries. Therefore, we consider downturn indicators at the TNIC-2 level, which is as coarse as 2-digit SIC codes.[12] The logic for the different aggregation levels is that the financial position of a specific product market is unlikely to trigger economic shocks in broader industries. More generally, by ensuring that our measures of downturns reflect aggregate contractions, we further alleviate concerns that we are capturing granular shocks that are systematically related to debt structure both horizontally and vertically.

Panel C of Table 1 reports summary statistics of our downturn indicators. Based on TNIC-2 industries, the severe (D_1^{ind}), medium (D_2^{ind}), and mild (D_3^{ind}) downturns account for 10.6%, 17.3%, and 26.0% of firm-quarter observations, respectively. Figure 1 shows the incidence of each indicator between 1996 and 2019. Because downturns are defined quarterly, we smooth the series into yearly frequency by computing the fraction of firm-quarters that experienced downturns in a given year. Figure 1 demonstrates that our downturn observations are largely clustered around known recession dates (shaded areas), indicating that our measure captures major historical economic shocks. Down-

[12] As in the 2-digit SIC case, the likelihood of two randomly chosen firms being in the same TNIC-2 industry is about 4.5%.

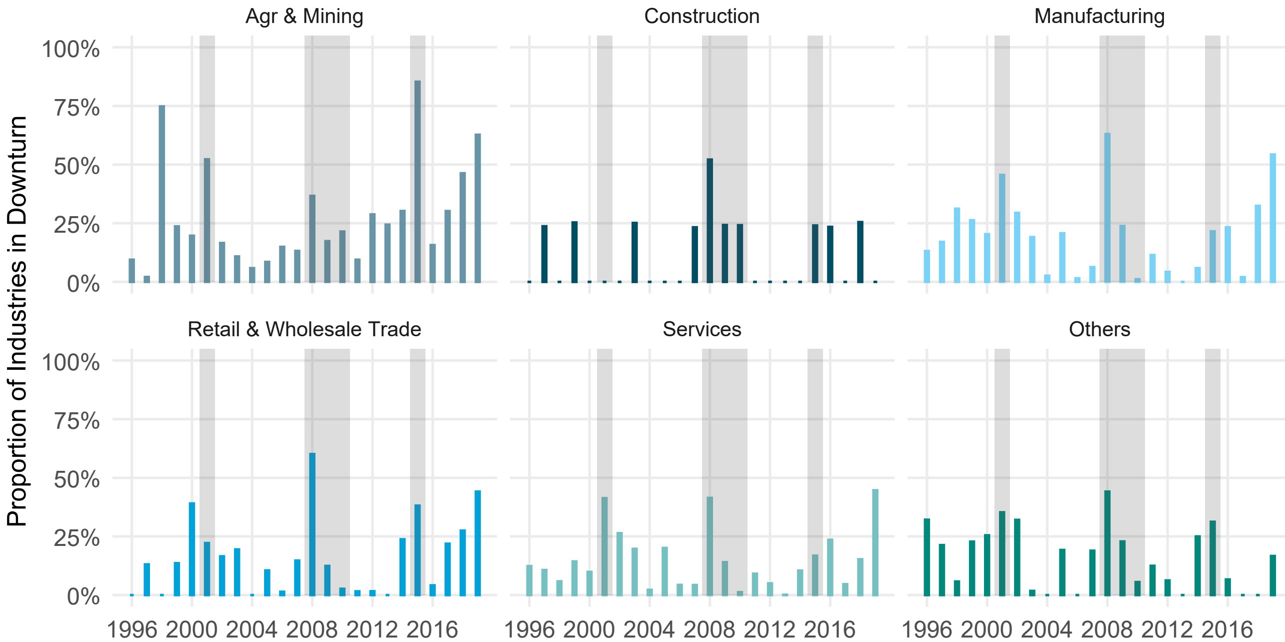

Figure 2. Time Series of Industry Downturns for Broad Sectors (1996–2019). This figure plots the annual time series of the proportion of firm-quarter observations experiencing an industry downturn according to downturn indicator variables D_2^{ind} across broad sectors of BEA industries. These variables indicate that a firm's industry peers experienced both negative median stock returns and median revenue growth in the bottom 33% of the distribution. Shaded areas denote NBER recession dates, except for the last one in 2015, which marks the commodity price bust.

turns peaked around 2008, when about 25% and 50% of firm-quarters experienced our most and least severe definitions of industry downturns, respectively.

Our robustness exercise using IO tables follows a similar procedure to compute downturn indicators based on fixed (BEA) industry classifications. Again, we construct downturn indicators at a broader level ("Summary," corresponding to approximately 3- and 4-digit NAICS) than the other industry-level variables ("Detail"). In this sample, the incidence of the most to the least severe downturns corresponds to 11.6%, 17.8%, and 30.0% of industry-quarter observations, respectively.

Although TNIC industries improve on fixed industry classifications, only the latter allow us to examine industry variables in specific sectors. Figure 2 reports the incidence of medium severity downturns (D_2^{ind}) over the sample years across six broad sectors. We aggregate quarterly downturns at yearly frequencies so that Figure 2 depicts the fraction of industry-quarters hit by negative shocks in each year. To classify granular industries into broader categories, we use 2-digit NAICS codes. We create five large categories: *Agriculture & Mining*, *Construction*, *Manufacturing*, *Retail & Wholesale Trade*, and *Services*. Industries that do not fall under these categories are classified as *Others*, resulting in a total of six sectors.

Figure 2 shows how aggregate contractions may have heterogeneous effects across sectors. For example, the Construction sector started experiencing the 2008 Great Recession before other sectors that were also severely hit, such as Manufacturing and Retail & Wholesale Trade. In contrast, Agriculture & Mining suffered milder effects in 2008. Still, it was later severely affected by the commodity price bust in 2015, with roughly 80% of its industries experiencing a downturn that year. Other noteworthy events observable in the figure are the 1997-1998 Asian Financial Crisis, which was particularly severe for the Agriculture sector, and the poor performance of Agriculture & Mining, Manufacturing, and Retail in 2019, partially due to trade wars between the U.S. and China during that year.[13] In sum, our measure of downturns is capable of capturing well-known, widespread and sector-specific contractions, therefore ruling out concerns it reflects particularities of our empirical strategy.

2.4 Baseline Specification

We estimate how cross-supplier variation in long-term debt structure affects the impact of industry downturns on firms. We interpret the greater devaluations associated with upstream debt maturity as a downstream amplification channel of financial constraints. Importantly, we control for the horizontal amplification documented by Carvalho (2015), which stems from cross-sectional variation in peers' long-term debt structure. In our benchmark analysis, we use VTNIC networks to construct industry variables based on TNIC peers and supplier-related variables. We capture downstream amplification effects by estimating the following specification:

$$\begin{aligned} AbnRet_{i,t} = {} & \alpha_0 \cdot FC^{f}_{i,t} + \alpha_1 \cdot FC^{ind}_{i,t} + \alpha_2 \cdot FC^{sup}_{i,t} \\ & + \beta_0 \cdot \left[FC^{f}_{i,t} \times D^{ind}_{i,t}\right] + \beta_1 \cdot \left[FC^{ind}_{i,t} \times D^{ind}_{i,t}\right] + \beta_2 \cdot \left[FC^{sup}_{i,t} \times D^{ind}_{i,t}\right] \\ & + \delta_0^{'} \cdot X_{i,t} + \delta_1^{'} \cdot \left[X_{i,t} \times D^{ind}_{i,t}\right] + \sum_i \mu_i + \sum_i \sum_t [\mu_t \times D^{ind}_{i,t}] + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where the outcome $AbnRet_{i,t}$ is firm i's abnormal return in quarter t. $X_{i,t}$ is a vector of firm-quarter controls, μ_i denotes firm fixed effects, and μ_t stands for quarter fixed effects. $D^{ind}_{i,t}$ is one of the firm-

[13]See, e.g., *Barron's*, January 4, 2016, *"2015's Commodity catastrophe was unprecedented"*, *The Guardian*, July 24, 2015, *"Global mining industry faces up to a deep malaise"*, *Federal Reserve History*, November 22, 2013, *"Asian Financial Crisis"*, *Federal Reserve Bank of Minneapolis*, October 1, 1999, *"Not your father's farm recession"*, *Fox Business*, March 8, 2019, *"Retail apocalypse: 4,810 closures in first three months of 2019"*, *CBS News*, September 6, 2019, *"U.S. manufacturing is in a recession. What does that mean for the rest of the country?"*, *PBS News*, January 16, 2020, *"What is the toll of trade wars on U.S. agriculture?"*

quarter indicators of industry downturn. $FC^{f}_{i,t}$, $FC^{ind}_{i,t}$, and $FC^{sup}_{i,t}$ are firm-quarter indicators of firm, industry, and suppliers' financial constraints, respectively.

Equation (1) captures three sources of amplification effects, represented by the interactions of the downturn indicators with each of the financing constraint variables. First, β_0 estimates the direct amplification effects of firm i's financing constraint. A negative value of this coefficient indicates the extent to which firms suffer additional valuation losses during downturns when they have high fractions of long-term debt due at the time of these shocks, as documented by Almeida et al. (2012). Second, β_1 measures horizontal amplification: the net effect of negative externalities from product-market peers' financial constraints on firm i's valuation during industry downturns, as in Carvalho (2015). Finally, our specification introduces a link between firm i's economic distress and upstream financial constraints, captured by the interaction between FC^{sup} and D^{ind}. Therefore, β_2 estimates how firms are differentially affected by industry downturns when their suppliers are financially constrained. A negative value of β_2 can be interpreted as the amplification of aggregate downturns due to the downstream propagation of financing constraints, which is the main focus of our analysis.

Firm controls in Equation (1) closely follow the related literature and include *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, and *Tangibility*. We also add industry controls, including *Industry Leverage*, HHI^{ind}, *Industry Asset Maturity*, and one-, two-, and three-lag terms of *Industry Revenue Growth*. All industry-related variables and suppliers' financing constraint indicators are at the firm level due to the structure of TNIC and VTNIC networks. Moreover, all controls and time fixed effects are interacted with the downturn indicators.[14] Interactions between controls and D^{ind} allow for heterogeneous sensitivity to shocks across firms based on observable characteristics. This ensures that β_0, β_1, and β_2 do not capture the sensitivity to downturns coming from control variables. In addition, including downturn-quarter fixed effects implies that estimation of β_2 relies on cross-supplier variation in long-term debt maturity across firms experiencing downturns in the same quarter.[15] Finally, we add firm fixed effects to absorb any unobservable, time-invariant firm characteristics, such as a firm's tendency to have constrained suppliers and to experience worse downturns.

[14] *Downturn–Quarter* fixed effects is the interaction of quarter-specific effects and downturn indicators.

[15] The inclusion of downturn-quarter-specific effects also implies that direct effects of industry downturns cannot be estimated, and thus the corresponding term was removed from Equation (1).

3 Results

3.1 Baseline Results: Downstream Amplification

Table 2 reports estimates of β_2 from Equation (1). Panels A and B report coefficients of interactions of each downturn indicator with FC_{50}^{sup} and FC_{33}^{sup}, respectively. In each panel, columns (2), (4), and (6) include firm fixed effects. Across all specifications, the estimates are negative and statistically significant. For our mild definition of a downturn in column (6), the estimates indicate that firms suffer an additional loss of 1.08 percentage points (p.p.) in abnormal returns during downturns when their suppliers' long-term debt maturing is above the median. Comparing the top and bottom terciles of this distribution, the results show an additional 1.44 p.p. devaluation. Comparisons of point estimates of β_2 across columns and panels show that the estimated effects are monotonic in the severity of the downturn and the degree of upstream financing constraints.

— PLACE TABLE 2 ABOUT HERE —

To more accurately assess the economic magnitude of these effects, Table 2 reports amplification effects due to supplier constraints. Following Carvalho (2015), these figures capture the relative increase in the impact of downturns implied by the estimates of β_2. For instance, the coefficient in column (6) of Panel A translates into an 11% amplification of industry negative shocks, implying a financial multiplier of 1.1. To compute these values, we scale the estimated β_2 by the total effect of the downturn on firms with unconstrained suppliers. To obtain these total effects, we estimate specifications similar to (1), imposing the restriction that $FC_{50}^{sup} = 0$ and replacing downturn–quarter fixed effects with quarter fixed effects. In these regressions, the total effect of downturns is given by the coefficient on the downturn indicator plus the average of the variables interacted with it, each multiplied by its respective interaction coefficient. The values in Table 2 reveal economically sizable effects, especially for severe downturns and more constrained suppliers. In Panel A, the average amplification effect is 14.6% across columns (2), (4), and (6) with firm fixed effects included, while this average is 18.7% in Panel B.

— PLACE TABLE 3 ABOUT HERE —

To put our findings into context, Table 3 reports estimates of direct and horizontal amplification effects of financing constraints previously documented by Almeida et al. (2012) and Carvalho (2015) for

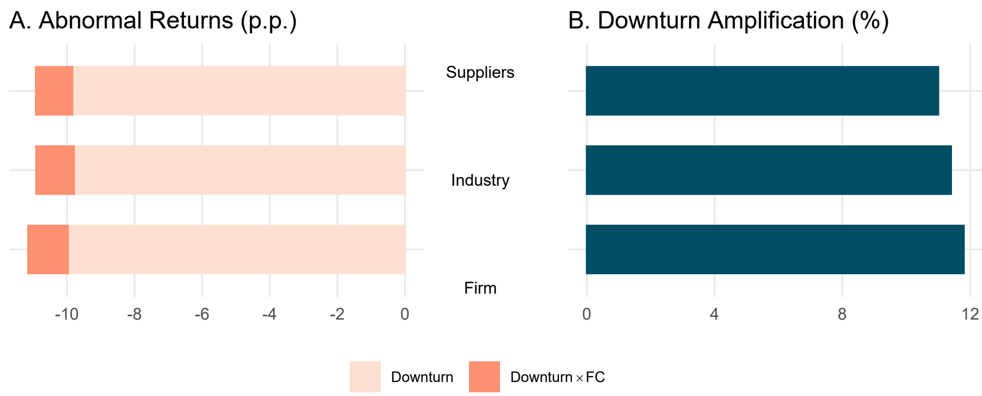

Figure 3. Three Dimensions of Downturn Amplification via Financing Constraints. This figure plots the estimated coefficients reported in Table 3 relative to the differential sensitivities to downturns stemming from financial distress of firms themselves, of their industry peers, and of their suppliers. Panel A shows the additional devaluation experienced by firms during downturns due to each channel, and Panel B reports the corresponding amplification effects.

our preferred specification—column (6) of Panel A in Table 2. Specifically, Table 3 reports differential sensitivities to downturns arising from financial distress among firms themselves, their industry peers, and their suppliers. The first column reports the total direct effect of D_3^{ind} on the subsample where the indicator specified in each row equals zero. Below these coefficients, we report corresponding p-values from Wald tests of linear restrictions on regression parameters. The second column reports estimates of β_0, β_1, and β_2 in Equation (1), while the last column reports the respective amplification effects.

Results show that firms in the top tercile of the yearly fraction of long-term debt maturing ($FC^f = 1$) experience 1.18 p.p. lower abnormal returns during industry downturns, corresponding to an amplification effect of 11.8%. Further, firms above the median of the yearly fraction of industry peers with debt largely due ($FC_{50}^{ind} = 1$) suffer an additional valuation loss of 1.12 p.p., implying an amplification effect of 11.4%. The size of these estimates suggests that the downstream amplification is roughly equal to the horizontal amplification effect in our baseline specification. These results are summarized in Figure 3. In Panel A, the lighter shades measure the total effect of the downturn on firms when each amplification channel is shut down. The darker shades show the additional devaluation experienced by firms when each channel is present, and Panel B reports the corresponding amplification effect. Overall, the estimates are relatively similar across amplification channels, with the firm's own debt maturity effect slightly larger, followed by horizontal amplification.

Finally, we also estimate Equation (1) using a continuous version of our supplier financing constraint variable. To capture our main effect, we interact our downturn indicators with the continuous variable FC^{sup} rather than with quantile indicators. Table C.1 in the Appendix reports estimates of β_2 in this framework. The results are qualitatively similar to those using our indicator variable approach. We also replicate our main results using measures of horizontal and upstream financing constraints based on TNIC and VTNIC pairwise similarity scores, thereby accounting for the intensity of these linkages. We describe this procedure in detail and report results in Appendix B.

4 Heterogeneous Effects

This section characterizes the baseline results by examining cross-sectional heterogeneity in observable characteristics of both the focal firms and their potential suppliers identified through VTNIC connections. The analysis sheds light on the mechanisms driving downstream amplification and the conditions under which the vertical financing constraint channel operates more strongly.

4.1 Suppliers' Reliance on Long-Term Debt

As discussed in Almeida et al. (2012), a high fraction of long-term debt due at a given moment should be a binding constraint only when long-term debt is sizable on a firm's balance sheet. Following this reasoning, we classify firms with a one-year lagged ratio of total long-term debt to total assets above 5% as more exposed to maturity constraints (Carvalho (2015)). Crucially, our main results should be driven by the long-term debt structure of *suppliers* that are considered financially constrained. As such, firms that do not rely on long-term debt should still be exposed to downstream amplification if their constrained suppliers are. To formalize this notion, we define the following variable for firm i at quarter t:

$$FCHD_{i,t}^{sup} = \frac{\sum_{k \in S(i,t)} FC_{k,t}^{f} \cdot HD_{k,t}}{\sum_{k \in S(i,t)} FC_{k,t}^{f}},$$

where $HD_{k,t}$ is an indicator that equals one when supplier k's total long-term debt is at least 5% of total assets. Thus, $FCHD^{sup}$ is the fraction of constrained suppliers that rely substantially on long-term debt, as defined by the aforementioned classification. If our identification strategy is valid, this variable should drive our baseline results. However, firms that rely on high-debt suppliers might have different sensitivity to downturns for reasons unrelated to upstream financing constraints. In such a case, including $FCHD^{sup}$ alone in our regressions could contaminate our estimate of interest with these omitted factors. We control for this with $HD^{sup}_{i,t}$, which is the firm-level overall fraction of suppliers with long-term debt to total assets above 5%. We then construct a triple-differences (DDD) model by adding these variables and their interactions to our baseline specification (Equation (1)), estimating the following regression model:

$$\begin{aligned}
AbnRet_{i,t} &= \alpha_0 \cdot FC^{f}_{i,t} + \alpha_1 \cdot FC^{ind}_{i,t} + \alpha_2 \cdot FC^{sup}_{i,t} + \alpha_3 \cdot FCHD^{sup}_{i,t} \\
&+ \beta_0 \cdot \left[FC^{f}_{i,t} \times D^{ind}_{i,t}\right] + \beta_1 \cdot \left[FC^{ind}_{i,t} \times D^{ind}_{i,t}\right] + \beta_2 \cdot \left[FC^{sup}_{i,t} \times D^{ind}_{i,t}\right] \\
&+ \beta_3 \cdot \left[FC^{sup}_{i,t} \times FCHD^{sup}_{i,t}\right] + \beta_4 \cdot \left[FCHD^{sup}_{i,t} \times D^{ind}_{i,t}\right] \\
&+ \gamma \cdot \left[FC^{sup}_{i,t} \times D^{ind}_{i,t} \times FCHD^{sup}_{i,t}\right] \\
&+ \delta_0' \cdot X_{i,t} + \delta_1' \cdot \left[X_{i,t} \times D^{ind}_{i,t}\right] + \sum_i \mu_i + \sum_i \sum_t [\mu_t \times D^{ind}_{i,t}] + \epsilon_{i,t}.
\end{aligned} \tag{2}$$

Compared with our baseline regression in Equation (1), Equation (2) adds six terms. Four terms correspond to adding $FCHD^{sup}$ as a control, its interactions with FC^{sup} and D^{ind}, and the corresponding triple interaction. The other two terms correspond to HD^{sup} as a control and its interaction with D^{ind}, which are subsumed into the vector of controls for ease of exposition.[16] Here, the coefficient of interest is γ, which measures the sensitivity of our baseline result to cross-sectional variation in the importance of long-term debt across constrained suppliers.

— PLACE TABLE 4 ABOUT HERE —

Table 4 reports estimates of the triple interaction coefficient in Equation (2). Estimates are negative across all models and statistically significant under our strict and intermediate definitions of downturns. Qualitatively, these results suggest that our baseline effects are stronger when a greater share of firms' constrained suppliers rely more on long-term debt. More precisely, the results imply that a one-standard-deviation increase in $FCHD^{sup}$ is associated with abnormal returns that are 0.43–1.40 p.p. lower during industry downturns driven by suppliers' constraints. This result underscores the importance of long-term debt in our main results, serving as a sanity

[16] Our results are qualitatively similar if we define HD^{sup} as the fraction of *unconstrained* suppliers with long-term debt to total assets above 5%. This also holds for the similar exercises we report in the next sections.

check that customers of firms that are more likely to be constrained according to our identification strategy are more exposed to downstream amplification.

4.2 Trade Credit

Garcia-Appendini and Montoriol-Garriga (2013) show evidence that firms build cash reserves to provide liquidity to distressed clients in the form of trade credit. In addition, Almeida et al. (2024) show that short-term investment by firms that rely heavily on supplier financing is more sensitive to funding frictions. Together, these results suggest that financing constraints can propagate downstream because constrained suppliers have limited capacity to extend credit to their clients. We directly test this hypothesis in this section.

Because pairwise supplier-customer provision of trade credit is not directly observed in the data, we proxy it with downstream firms' accounts payable and upstream firms' accounts receivable, as in Garcia-Appendini and Montoriol-Garriga (2013) and others. To test our conjecture, we construct two variables. First, we define Pay^f as a firm's accounts payable (Compustat's `apq`) scaled by its cost of goods sold (`cogsq`). This variable proxies for the use of trade credit by downstream firms. Second, we define $FCRec^f$ as a firm's accounts receivable (`rectq`) scaled by sales (`saleq`), which proxies for a firm's supply of trade credit to its customers. We use $FCRec^f$ to compute a customer-level measure of upstream-constrained firms' supply of trade credit, $FCRec^{sup}$, as follows:

$$FCRec_{i,t}^{sup} = \frac{\sum\limits_{k \in S(i,t)} FC_{k,t}^{f} \cdot FCRec_{k,t}^{f}}{\sum\limits_{k \in S(i,t)} FC_{k,t}^{f}}.$$

Thus, $FCRec_{i,t}^{sup}$ is the average measure of trade credit offered by firm i's constrained suppliers in quarter t. We estimate two triple-difference specifications that interact each measure of trade credit with our indicators of upstream financing constraints and industry downturns, as in Equation (2). For the specification with $FCRec^{sup}$, we further include Rec^{sup}, the average value of receivables scaled by sales across all upstream firms, and its interactions with the downturn indicators, as in Section 4.1. The coefficients on the triple interaction terms measure the sensitivity of our baseline amplification effects to our proxies for trade credit available to downstream firms. To facilitate interpretation, we scale both Pay^f and $FCRec^{sup}$ by their sample standard deviations.

Table 5 reports the results of this exercise. Panels A and B report the estimates of the triple-interaction coefficients with Pay^f and $FCRec^{sup}$, respectively. For both measures of trade credit and all downturn intensities, the triple-difference coefficients are positive and significant. The estimates are economically meaningful: a one standard deviation increase in Pay^f is associated with 1.72–1.86 p.p. higher abnormal returns during downturns in which suppliers are classified as financially constrained, whereas a one standard deviation increase in $FCRec^{sup}$ is associated with 1.32–1.90 p.p. higher abnormal returns.

— PLACE TABLE 5 ABOUT HERE —

As in Almeida et al. (2024), higher levels of trade credit can imply greater reliance on supplier financing, which should translate into *stronger* amplification effects. Our specifications address this concern in two ways. First, the inclusion of firm fixed effects controls for each firm's average level of trade credit usage, absorbing any persistent differences in reliance on supplier financing from both overall suppliers and constrained ones. Second, in Panel B, we directly control for the differential sensitivity to downturns among firms that rely more on supplier financing, regardless of upstream financial constraints, by including Rec^{sup} and its interactions with the downturn indicators. As a result, the coefficients in Table 5 represent differential effects driven by deviations from firm-specific and downturn-quarter levels of trade credit, showing that amplification is weaker when suppliers can maintain credit provision to customers. These findings are consistent with suppliers' reduced capacity to extend trade credit to customers being a key mechanism driving downstream amplification.

4.3 Input Specificity

Barrot and Sauvagnat (2016) show that input specificity is a key driver of the downstream propagation of shocks. As firms rely more on specific inputs, they incur higher switching costs, making vertical relationships more rigid from a downstream perspective. In addition to direct propagation effects, greater dependence on particular suppliers may increase exposure to their financial soundness, also modulating amplification effects.

Following Barrot and Sauvagnat (2016), we proxy product specificity with R&D expenditures, as innovation-intensive firms typically produce more specialized products that are difficult for customers to substitute. As in Custódio et al. (2023), we compute this measure by scaling Compustat's quarterly research and development expenses (`xrdq`) by total assets.[17]

As in Section 4.1, what should matter for our proposed channel is the specificity of inputs purchased exclusively from constrained suppliers. Thus, we compute our measure of interest as follows:

$$FCRD_{i,t}^{sup} = \frac{\sum\limits_{k \in S(i,t)} FC_{k,t}^{f} \cdot RD_{k,t}}{\sum\limits_{k \in S(i,t)} FC_{k,t}^{f}},$$

where $RD_{k,t}$ is a variable that indicates whether firm k is R&D intensive, defined as being in the top 50% of R&D expenses scaled by assets in quarter t.[18] Thus, $FCRD_{i,t}^{sup}$ is the fraction of firm i's constrained suppliers that are R&D intensive. Consistent with our previous heterogeneity exercises, we estimate a DDD model in which the triple interaction includes the industry downturn indicator, the suppliers' financial constraint indicator, and $FCRD^{sup}$. Again, we control for possible differential sensitivity to downturns by including the overall fraction of suppliers classified as R&D intensive and its interaction with the downturn indicators. The coefficient on this triple interaction measures how our baseline amplification effect varies with the R&D intensity of constrained suppliers.

— PLACE TABLE 6 ABOUT HERE —

Table 6 reports the results. The triple interaction coefficient is negative and highly statistically significant across all specifications. The estimates indicate that a one-standard-deviation increase in $FCRD^{sup}$ is associated with an additional devaluation of 0.90 to 2.52 p.p. for firms experiencing downturns when they rely on high-maturity suppliers. These results suggest that downstream amplification of negative shocks is stronger when firms rely more on suppliers of specialized inputs, consistent with Barrot and Sauvagnat (2016) and Custódio et al. (2023). The latter paper further finds that clients tend to substitute

[17] Following common practice in the literature (e.g., Lewis and Tan (2016); Campello et al. (2022)), we set missing values of R&D expenses to zero.

[18] The results are qualitatively similar if we consider quarterly distributions of firm i's suppliers, in which case the classification of high-R&D suppliers depends on the downstream firm. The results also hold if we consider the value of R&D expenses scaled by assets instead of indicators.

away from financially constrained suppliers, but less so when these suppliers provide specific inputs. Our results complement their findings by showing that this rigidity in vertical relationships due to input specificity can be costly for clients by increasing their exposure to upstream financial distress.

4.4 Suppliers' Concentration

Next, we examine how our baseline results depend on the level of upstream concentration. When suppliers vary substantially in size, larger suppliers are more likely to provide specialized inputs. In this context, suppliers' overall concentration would also serve as a proxy for firms' input specificity. In addition, highly concentrated suppliers can translate into lower bargaining power and worse outside options for customers. Either way, a higher concentration would increase firms' costs of switching suppliers. In this scenario, we should see stronger amplification of downturns when upstream concentration is higher. Since we do not observe pairwise transactions between each customer and its suppliers, we construct a customer-level HHI index based on suppliers' quarterly revenues $Rev_{k,t}$ (Compustat item `revtq`). Specifically, firm i's upstream concentration in period t is given by:

$$HHI_{i,t}^{sup} = \sum_{k \in S(i,t)} \left(\frac{Rev_{k,t}}{\sum_{\omega \in S(i,t)} Rev_{\omega,t}} \right)^2 .$$

We include this continuous variable in a DDD specification similar to our previous exercises. In this model, the coefficient on the triple interaction captures the sensitivity of the amplification effect to cross-sectional variation in firms' supplier concentration.

— PLACE TABLE 7 ABOUT HERE —

The estimates of the DDD interaction are reported in Table 7. The coefficients are negative across all specifications and significant at the 5% level under the severe and medium downturn definitions. These estimates indicate that a one-standard-deviation increase in HHI^{sup} is associated with lower abnormal returns of 0.69 to 1.46 p.p., driven by downstream amplification. These results provide further evidence that firms are more exposed to upstream financial distress when switching costs are higher.

5 Real Effects

The valuation effects documented thus far demonstrate that upstream financial constraints amplify industry downturns across multiple dimensions. This section investigates the real effects underlying these valuation impacts, examining whether supplier financial constraints manifest as significant changes in operational outcomes. First, we examine typical corporate policies and operational outcomes using firms' balance sheets. Second, we examine product market and supply chain aspects in greater detail by decomposing revenues into prices and quantities sold in a subsample of consumer product manufacturers.

5.1 Balance Sheets

As Carvalho (2015) notes, horizontal propagation of financing constraints operates through declining asset values within industries, which restricts peers' ability to raise external funds. As a result, the whole sector suffers from limited access to liquidity, leaving it more exposed to downturns. As supporting evidence for this conjecture, the author documents that horizontal amplification is also detrimental to investment levels and asset values. In contrast, downstream amplification through financing constraints should primarily affect supply chain operations and output levels. This notion is supported by Barrot and Sauvagnat (2016), who show that supply chain disruptions lead to significant decreases in the output of customer firms. If our baseline empirical approach is indeed capturing a distinct amplification channel, these fundamental differences in real outcomes should manifest on firms' balance sheets.

We test whether our baseline effects are present in outcomes related to investment and operations. In particular, we estimate Equation (1) using four dependent variables constructed from balance sheet information. First, we test outcomes directly related to production operations: *Change in Sales by Assets* and *Change in Costs by Assets*. Second, we test two measures of investment and disinvestment: *Investment Change* and *Change in Asset Sale*.

Table 8 reports the results of this exercise. In these specifications, we use FC_{50}^{sup} as our upstream financing constraint indicator.[19] Panels A and B show negative and significant effects on both sales and

[19] Results available upon request show a qualitatively similar and quantitatively more pronounced effect using FC_{33}^{sup}.

cost measures. Column (6) shows that firms with constrained suppliers during industry downturns experience 0.28 p.p. and 0.29 p.p. lower changes in sales and costs scaled by assets, respectively, corresponding to 2.8% and 3.5% of their respective sample standard deviations. Panel C reports results with *Investment Change* as the dependent variable. In stark contrast to operational outcomes, we find positive coefficients across all specifications, and they are highly statistically significant for our severe and medium downturn indicators. The estimate in column (4) implies that firms increase investment growth by 0.54 p.p. relative to total assets, which corresponds to 3.6% of the sample standard deviation. Finally, Panel D reports negligible and statistically insignificant effects on asset sales.

— PLACE TABLE 8 ABOUT HERE —

In this exercise, the results reveal nuanced effects of downstream financial constraints on firms' balance sheets. Production-related variables, such as costs and sales, show evidence of supply chain disruptions, with firms buying less from suppliers and selling less in their own markets. Conversely, the evidence indicates increased investment, plausibly reflecting downstream firms' efforts to build capital and reduce long-term reliance on supplier financing. These results highlight how production and investment outcomes are differentially affected by downstream amplification, with suppliers' restricted liquidity provision disrupting customers' operations while forcing investment in capital. Contrasting these findings with those of Carvalho (2015) suggests that although both horizontal and downstream financing constraints aggravate the valuation effects of adverse shocks, they do so through different channels.

5.2 Product Prices and Quantities

One limitation of standard firm-level data (e.g., Compustat) is the lack of granularity needed to investigate firms' product-market operations at finer levels. While our results in Section 5.1 suggest downstream amplification effects on firms' real-side operations, they obscure the role of firms' product prices and quantities in their total revenues. In this section, we leverage granular retail data for a subset of the firms in the sample to go beyond the typical firm-level analysis of financial amplification, disentangling sales into price and quantity margins.

5.2.1 NielsenIQ Retail Scanner Sample

We obtain product-level sales data from the NielsenIQ Retail Scanner database, available through the Kilts Center for Marketing Data at the University of Chicago Booth School of Business. The dataset reports product-level sales recorded by scanners in 30,000 to 50,000 U.S. retail stores across more than 2,700 counties. The unit of observation in the raw data is product-store-week sales, beginning in January 2006. Each product is uniquely identified by its Universal Product Code (UPC), corresponding to its barcode. We identify manufacturers of each product using information from the GS1 U.S. Data Hub, the official organization responsible for issuing UPCs in the U.S. Producers that need to assign UPCs to their products must purchase a company prefix from GS1, a five- to ten-digit number that is placed at the beginning of any UPC belonging to its respective firm.

Using a comprehensive list of prefixes from GS1, we map over 80% of UPCs in retail scanners to over 50,000 manufacturers' names, including public and private firms. Next, we match company names to Compustat using the fuzzy matching algorithm proposed by Schoenle (2017), also used by Argente et al. (2017). From our original Compustat sample, we identify 754 firms as product manufacturers in the NielsenIQ dataset.[20] While incorporating Retail Scanner data considerably diminishes our sample by focusing only on manufacturers of consumer goods, these firms are at the bottom of the production chain and manufacture products sold directly to consumers. As such, they are well-exposed to supply chain shocks and disruptions, providing an ideal setting to examine how supplier financial constraints affect pricing and production outcomes. In addition, these firms are large and have extensive product portfolios, covering a total of 181,740 unique UPCs, therefore ensuring a sizable sample for our empirical tests.

For each unique UPC in our sample, we sum the number of units sold and total revenue generated across all stores for each calendar quarter. We further divide revenues by quantities to obtain a quarterly sales-weighted average price of the product. The resulting final sample consists of 2,297,018 product-quarter observations. Finally, we estimate Equation (1) with the natural log of revenues, quantities, and prices as dependent variables. To ensure that the estimates rely on within-product comparisons, the specifications include UPC fixed effects in addition to downturn-quarter fixed effects.

[20] This coverage is consistent with other papers that match NielsenIQ to Compustat over a similar time window, such as Hajda and Nikolov (2022).

5.2.2 Product-Level Evidence

Table 9 reports estimates from our product-level specification.[21] Columns (1)–(3) report negative, statistically significant effects on total revenues across all downturn indicators. For instance, column (2) estimates 19.3% lower revenues for products of firms experiencing industry downturns when their suppliers are financially constrained. Similar patterns emerge for quantities in columns (4)–(6), with column (5) showing 23.2% lower quantities sold. Finally, we find positive, significant estimates for prices in columns (7) and (8), with the latter implying 5.1% higher prices.

— PLACE TABLE 9 ABOUT HERE —

The estimates in Table 9 reveal several patterns. First, we confirm our results on sales reported in Table 8, showing consistency across our firm- and product-level samples. Second, lower revenues are driven by lower quantities sold. Third, in more severe industry downturns, increases in product prices partially offset the effect of lower quantities sold on revenues. Although production costs are not observed at the same level of granularity as sales for these firms, the results in Table 8 show that lower sales are associated with lower production costs. Therefore, the results are consistent with shortages in supplier financing disrupting firms' production levels, leading firms to increase prices to partially offset losses from lower quantities produced. To the extent that upstream debt maturity is exogenous to the timing of industry downturns, the results in Table 9 represent departures from firms' optimal long-run production and pricing strategies. The comprehensive evidence on valuation losses from the baseline results further supports this interpretation.

Our findings using retailer data suggest that lower production levels due to supplier credit constraints lead firms to raise prices. However, the related literature provides evidence for the "fire sale" hypothesis, whereby firms experiencing credit shocks cut prices to liquidate inventories and generate short-term cash flows (Kim (2020); Lenzu et al. (2024)). In our context, however, if the results indeed reflect involuntary lower production due to input disruptions, firms do not necessarily have incentives to lower prices, which could further reduce revenues. Still, these related findings suggest that inven-

[21] To obtain precise percentage changes rather than linear approximations, the coefficients in Table 9 are transformed to $100(e^{\beta} - 1)$, where β is the coefficient from the original regressions with logged dependent variables. This transformation implies that the revenue decomposition is not exact: the sum of the coefficients from the regressions on quantities and prices is approximately equal to the coefficient from the regression on revenues.

tory levels during credit shocks influence firms' pricing policies. To better relate their findings to ours, we test for the fire sales hypothesis within our empirical framework.

We rely on the notion that firms' production capacity is primarily determined by existing inventory during shocks (Almeida et al. (2024)). Specifically, we define *Invent* as Compustat's `invtq` scaled by lagged assets to measure the firm's inventory value in a given quarter. We then build a triple-differences model that interacts lagged *Invent* with our industry downturns and suppliers' financial constraint indicators, as we do in Section 4. The triple-differences coefficient thus estimates the sensitivity of our results in Table 9 to the firm's previously accumulated inventory. Table 10 reports the results of this heterogeneity analysis.

— PLACE TABLE 10 ABOUT HERE —

Columns (1)–(6) report positive sensitivity of product revenues and quantities to inventory, with revenue estimates statistically significant for our medium and mild definitions of downturns, and quantities statistically significant in all models. The estimates in columns (2) and (5) imply that a one standard deviation increase in *invent* is associated with approximately 23.5% and 25.6% increases in revenues and quantities sold, respectively. In contrast, we find a negative response of prices to inventories, albeit significant only for our strictest downturn indicator, where a standard deviation increase in *invent* implies roughly 9.4% lower prices.

Although limited to a subsample of firms, our results with retail data on consumer goods shed further light on how disruptions in supplier financing affect firms' operations during industry downturns. Overall, we find that the valuation losses documented in our baseline results are driven by lower sales that are partially offset by higher product prices. However, these results are significantly alleviated for firms that held relatively high levels of inventory during the downturns. These findings can be rationalized by accumulated short-term investments allowing the firm to maintain production capacity via a working capital channel (Almeida et al. (2024)) or by firms liquidating product stocks to generate revenues (Kim (2020); Lenzu et al. (2024)). Either way, the collective evidence suggests that inventories act as a cushion for supplier credit-constrained firms to maintain production levels instead of absorbing shocks with increases in product prices.

6 Concluding Remarks

Financial constraints do not remain confined within firm boundaries—they travel through production networks with amplifying force. This paper uncovers a previously undocumented downstream channel through which supplier financial distress propagates to customers, demonstrating that upstream financing constraints magnify industry downturns by 11% to 17% in valuation losses. These findings reveal that downstream firms' exposure to aggregate shocks depends critically on the financial health of upstream firms, extending our understanding of how credit market frictions cascade through production networks.

The evidence from our heterogeneity analysis reveals several underlying forces that modulate these effects. Downstream amplification intensifies when suppliers carry heavier long-term debt burdens and when customers face higher switching costs and greater dependence on existing relationships. Trade credit emerges as the underlying mechanism: firms with continued access to supplier financing weather downturns more effectively, while those cut off from this liquidity channel suffer disproportionately. On the real side, the effects are asymmetric: revenues and costs contract as production capacity shrinks, yet investment rises as firms strategically build capital to reduce their vulnerability to constrained suppliers. Product-level evidence sheds further light on these findings, showing that quantity reductions drive revenue declines while firms raise prices to partially offset losses—except when existing inventories provide a cushion that preserves both output and pricing stability.

These findings carry direct implications for crisis management and policymaking. Interventions that facilitate trade credit provision in upstream industries and support inventory financing in downstream sectors can alleviate the cascading effects of financial distress during economic contractions. More broadly, the results underscore that effective crisis response must look beyond individual firm balance sheets to the network of relationships that sustain production. Future research can build on these insights to examine optimal policy mechanisms and explore how strategic inventory management can serve as a first line of defense against supply chain shocks.

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Table 1. Summary Statistics This table reports summary statistics for the variables used in our main sample. The sample covers 274,313 firm-quarter observations during the period from 1996 to 2019. Panel A reports statistics for firm variables. *Abnormal Return*, *Investment Change*, *Change in Costs by Assets*, *Change in Sales by Assets*, and *Change in Asset Sale* are measured in percentage points. Panels B and C report variables for industries identified by the Text-based Network Industry Classification (TNIC) (Hoberg and Phillips (2010, 2016)). Panel B reports statistics for TNIC-3 industries, which are as granular as 3-digit SIC codes. Panel C reports statistics for our industry downturn measures based on TNIC-2 industries, which are as granular as 2-digit SIC codes. Due to the structure of the TNIC database, industry variables are constructed at the firm level. For details on variables construction, see Section 2.1 and Section 2.3.

A. Firm Variables	Mean	Median	Std. Deviation	Observations
Abnormal Return	−0.198	−2.341	31.541	266,766
Q	2.277	1.529	2.788	274,313
Cash Flow	0.005	0.026	0.098	258,604
Cash	0.206	0.103	0.241	274,313
Size	5.640	5.562	2.083	274,313
Rated	0.213	0.000	0.409	274,313
Investment Grade	0.067	0.000	0.250	274,313
Leverage	0.234	0.180	0.279	266,238
Tangibility	0.267	0.186	0.243	273,834
Investment Change	−1.150	−0.118	14.845	258,013
Change in Costs by Assets	−0.589	−0.019	8.314	255,417
Change in Sales by Assets	−0.774	0.000	10.004	263,375
Change in Asset Sale	0.017	0.000	3.273	209,046
B. Industry Variables (TNIC-3)	Mean	Median	Std. Deviation	Observations
Industry Leverage	0.229	0.206	0.147	273,673
HHI	0.335	0.219	0.290	274,035
Asset maturity	8.125	6.482	5.628	262,184
Industry Revenue Growth (1 lag)	0.018	0.024	0.176	265,120
Industry Revenue Growth (2 lags)	0.018	0.024	0.173	256,307
Industry Revenue Growth (3 lags)	0.018	0.024	0.171	247,605
C. Industry Variables (TNIC-2)	Mean	Median	Std. Deviation	Observations
D_1^{ind}	0.106	0.000	0.308	274,279
D_2^{ind}	0.173	0.000	0.378	274,279
D_3^{ind}	0.260	0.000	0.439	274,279

Table 2. Downstream Amplification of Downturns via the Supplier Financing Constraint Channel. This table reports estimates of β_2 in Equation (1) using firm-quarter observations from 1996–2019. The dependent variable is *Abnormal Return*—quarterly stock return minus that of a portfolio matched on size, book-to-market, and previous-quarter returns (Daniel et al. (1997)), in percentage points. FC^{sup} is the fraction of suppliers with long-term debt largely due (predicted in the previous year), where suppliers are identified by VTNIC networks (see Section 2.2). FC^{sup}_{50} (FC^{sup}_{33}) equals one if FC^{sup} is in the top 50% (tercile) of its yearly distribution, zero if bottom 50% (tercile), and missing otherwise for FC^{sup}_{33}. D^{ind}_1, D^{ind}_2, and D^{ind}_3 are firm-level industry downturn indicators of severe, medium, and mild downturns, respectively, based on TNIC-2 industries (cf. Section 2.3). Panels A and B report additional valuation losses during downturns when FC^{sup}_{50} and FC^{sup}_{33} equal one, respectively. Amplification (%) reports the downturn amplification implied by each point estimate. Firm controls: *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and FC^f. Industry controls (TNIC-3): *Industry Leverage*, *HHI*, *Asset Maturity*, one–three lags of *Industry Revenue Growth*, and FC^{ind}_{50}. All controls are interacted with the corresponding downturn indicator. See Sections 2.1 and 2.2 for variable definitions. Standard errors clustered at the firm level. *, **, and ***: 10%, 5%, and 1% statistical significance levels, respectively.

Panel A. Top *vs.* Bottom 50% Supplier Financing Constraints

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC^{sup}_{50} \times D^{ind}_1$	-1.680^{***}	-1.415^{***}				
	(0.457)	(0.469)				
$FC^{sup}_{50} \times D^{ind}_2$			-1.426^{***}	-1.321^{***}		
			(0.374)	(0.383)		
$FC^{sup}_{50} \times D^{ind}_3$					-1.147^{***}	-1.077^{***}
					(0.328)	(0.332)
Amplification (%)	21.3	17.4	16.9	15.5	11.6	11.0
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	167,490	167,490	167,490	167,490	167,490	167,490
Adjusted R^2	0.037	0.072	0.043	0.078	0.051	0.086

Panel B. Top *vs.* Bottom 33% Supplier Financing Constraints

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC^{sup}_{33} \times D^{ind}_1$	-2.177^{***}	-1.752^{***}				
	(0.601)	(0.615)				
$FC^{sup}_{33} \times D^{ind}_2$			-1.773^{***}	-1.464^{***}		
			(0.481)	(0.489)		
$FC^{sup}_{33} \times D^{ind}_3$					-1.543^{***}	-1.435^{***}
					(0.417)	(0.424)
Amplification (%)	30.7	23.3	23.3	17.8	16.3	15.1
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	108,385	108,385	108,385	108,385	108,385	108,385
Adjusted R^2	0.038	0.078	0.044	0.085	0.052	0.092

Table 3. Firm, Industry, and Suppliers' Financial Constraints Amplification of Downturns. This table reports downturn amplification effects implied by the estimates of β_0, β_1, and β_2 in Equation (1). The sample consists of firm-quarter observations during the period 1996 to 2019. The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), measured in percentage points. FC^f is a firm-level indicator that equals one if the firm is in the top tercile of the previous year's distribution of proportion of long-term debt maturing in one year. FC^{ind}_{50} is a firm-level indicator that equals one if the fraction of firms' industry peers where $FC^f = 1$ is in the top 50% of its yearly distribution, and zero otherwise, where industry peers are identified by TNIC-3 industries. FC^{sup}_{50} is a firm-level indicator variable that equals one if FC^{sup} is in the top 50% of its yearly distribution, and zero otherwise. FC^{sup} is the fraction of suppliers with long-term debt largely due as predicted in the previous year, where suppliers are identified by VTNIC networks. See Section 2.2 for details on financial constraint measurements. D^{ind}_3 is a firm-level industry downturn indicator based on TNIC-2 industries. See Section 2.3 for detailed definitions of downturn indicators. The first column reports the total effect of D^{ind}_3 on the subsample where the indicator specified by the row equals zero. This figure is obtained from regressions similar to Equation (1) with the restriction that the respective financing constraint indicator equals zero and with quarter fixed effects instead of downturn-quarter. The second column shows the interaction coefficient of D^{ind}_3 with the financing constraint specified by the row. The first, second, and third row correspond to β_0, β_1, and β_2 in Equation (1), respectively. The value on the third column is the ratio of the second to the first columns, reporting the amplification of downturn implied by the respective point estimate. Firm controls are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, and *Tangibility*. Firm-level industry controls based on TNIC-3 industries are *Industry Leverage*, *HHI*, *Asset Maturity*, and one, two, and three lags of *Industry Revenue Growth*. See Sections 2.1 for variable definitions. The specification includes interactions of all control variables with the industry downturn indicator and firm fixed effects. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Return		*Amplification (%)*
	$D^{ind}_3(FC = 0)$	$FC \times D^{ind}_3$	
FC^f	-9.973^{***}	-1.175^{***}	11.8
	(p=0.000)	(0.400)	
FC^{ind}_{50}	-9.791^{***}	-1.120^{**}	11.4
	(p=0.000)	(0.435)	
FC^{sup}_{50}	-9.840^{***}	-1.077^{***}	11.0
	(p=0.000)	(0.332)	

Table 4. Heterogeneity by Importance of Long-term Debt. This table reports output from the estimation of the triple interaction coefficient from a triple differences specification where we interact FC_{50}^{sup}, D^{ind}, and $FCHD^{sup}$. The sample consists of firm-quarter observations during the period 1996 to 2019. The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), measured in percentage points. FC_{50}^{sup} is a firm-level indicator variable that equals one if FC^{sup} is in the top 50% of its yearly distribution, and zero otherwise. FC^{sup} is the fraction of suppliers with long-term debt largely due as predicted in the previous year, where suppliers are identified by VTNIC networks. See Section 2.2 for details on financial constraint measurements. D_1^{ind}, D_2^{ind}, and D_3^{ind} are firm-level industry downturn indicators of severe, medium, and mild downturns, respectively, based on TNIC-2 industries. See Section 2.3 for detailed definitions of downturn indicators. $FCHD^{sup}$ is the fraction of firms' suppliers with long-term debt largely maturing for which long-term debt accounts for at least 5% of total assets, as described in Section 4.1. The regression further includes HD^{sup}—the overall firm-level fraction of suppliers with long-term debt corresponding to least 5% of total assets—and its interaction with the downturns indicators. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Firm-level industry controls based on TNIC-3 industries are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers financial constraint indicator FC_{50}^{ind}. See Sections 2.1 and 2.2 for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Return		
	(1)	(2)	(3)
$FC_{50}^{sup} \times D_1^{ind} \times FCHD^{sup}$	-7.981^{**}		
	(3.743)		
$FC_{50}^{sup} \times D_2^{ind} \times FCHD^{sup}$		-5.874^{**}	
		(2.831)	
$FC_{50}^{sup} \times D_3^{ind} \times FCHD^{sup}$			-2.450
			(2.375)
Downturn–Quarter FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	157,328	157,328	157,328
Adjusted R^2	0.071	0.078	0.086

Table 5. Heterogeneity by Trade Credit. This table reports output from the estimation of the triple interaction coefficient from a triple differences specification where we interact FC_{50}^{sup}, D^{ind}, and a measure of trade credit provision from suppliers to customers. The sample consists of firm-quarter observations during the period 1996 to 2019. The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), measured in percentage points. FC_{50}^{sup} is a firm-level indicator variable that equals one if FC^{sup} is in the top 50% of its yearly distribution, and zero otherwise. FC^{sup} is the fraction of suppliers with long-term debt largely due as predicted in the previous year, where suppliers are identified by VTNIC networks. See Section 2.2 for details on financial constraint measurements. D_1^{ind}, D_2^{ind}, and D_3^{ind} are firm-level industry downturn indicators of severe, medium, and mild downturns, respectively, based on TNIC-2 industries. See Section 2.3 for detailed definitions of downturn indicators. Panel A uses Pay^f as a proxy for downstream firms' use of trade credit provided by suppliers. Pay^f is the firm's value of payables (`apq`) scaled by cost of goods sold (`cogsq`). Panel B uses Rec^{sup} as a proxy for upstream constrained firms' supply of trade credit to clients. Rec^{sup} is the average value of receivables (`rectq`) scaled by sales (`saleq`) across a firm's financially constrained suppliers. Both Pay^f and Rec^{sup} are scaled by their sample standard deviations. For details on variable construction, see Section 4.2. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Firm-level industry controls based on TNIC-3 industries are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers' financial constraint indicator FC_{50}^{ind}. See Sections 2.1 and 2.2 for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Downstream firms' accounts payable

	Abnormal Return		
	(1)	(2)	(3)
$FC_{50}^{sup} \times D_1^{ind} \times Pay^f$	1.719*		
	(1.006)		
$FC_{50}^{sup} \times D_2^{ind} \times Pay^f$		1.816**	
		(0.840)	
$FC_{50}^{sup} \times D_3^{ind} \times Pay^f$			1.863***
			(0.668)
Downturn–Quarter FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	166,093	166,093	166,093
Adjusted R^2	0.117	0.124	0.131

Panel B. Upstream firms' accounts receivable

	Abnormal Return		
	(1)	(2)	(3)
$FC_{50}^{sup} \times D_1^{ind} \times FCRec^{sup}$	1.900**		
	(0.792)		
$FC_{50}^{sup} \times D_2^{ind} \times FCRec^{sup}$		1.699***	
		(0.491)	
$FC_{50}^{sup} \times D_3^{ind} \times FCRec^{sup}$			1.322***
			(0.430)
Downturn–Quarter FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	157,328	157,328	157,328
Adjusted R^2	0.071	0.078	0.086

Table 6. Heterogeneity by Input Specificity. This table reports output from the estimation of the triple interaction coefficient from a triple differences specification where we interact FC^{sup}_{50}, D^{ind}, and $FCRD^{sup}$. The sample consists of firm-quarter observations during the period 1996 to 2019. The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), measured in percentage points. FC^{sup}_{50} is a firm-level indicator variable that equals one if FC^{sup} is in the top 50% of its yearly distribution, and zero otherwise. FC^{sup} is the fraction of suppliers with long-term debt largely due as predicted in the previous year, where suppliers are identified by VTNIC networks. See Section 2.2 for details on financial constraint measurements. D^{ind}_1, D^{ind}_2, and D^{ind}_3 are firm-level industry downturn indicators of severe, medium, and mild downturns, respectively, based on TNIC-2 industries. See Section 2.3 for detailed definitions of downturn indicators. $FCRD^{sup}$ is the fraction of firms' suppliers with long-term debt largely maturing that belong to the top 50% distribution of R&D expenses by quarter, as described in Section 4.3. The specification further includes the overall fraction of firm's suppliers that are classified as high R&D and its interaction with the downturn indicators. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Firm-level industry controls based on TNIC-3 industries are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers financial constraint indicator FC^{ind}_{50}. See Sections 2.1 and 2.2 for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Return		
	(1)	(2)	(3)
$FC^{sup}_{50} \times D^{ind}_1 \times FCRD^{sup}$	-14.598^{***}		
	(3.802)		
$FC^{sup}_{50} \times D^{ind}_2 \times FCRD^{sup}$		-8.101^{***}	
		(2.965)	
$FC^{sup}_{50} \times D^{ind}_3 \times FCRD^{sup}$			-5.186^{**}
			(2.455)
Downturn–Quarter FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	157,328	157,328	157,328
Adjusted R^2	0.071	0.078	0.086

Table 7. Heterogeneity by Suppliers Concentration. This table reports output from the estimation of the triple interaction coefficient from a triple differences specification where we interact FC^{sup}_{50}, D^{ind}, and HHI^{sup}. The sample consists of firm-quarter observations during the period 1996 to 2019. The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), measured in percentage points. FC^{sup}_{50} is a firm-level indicator variable that equals one if FC^{sup} is in the top 50% of its yearly distribution, and zero otherwise. FC^{sup} is the fraction of suppliers with long-term debt largely due as predicted in the previous year, where suppliers are identified by VTNIC networks. See Section 2.2 for details on financial constraint measurements. D^{ind}_1, D^{ind}_2, and D^{ind}_3 are firm-level industry downturn indicators of severe, medium, and mild downturns, respectively, based on TNIC-2 industries. See Section 2.3 for detailed definitions of downturn indicators. HHI^{sup} is a firm-level Herfindahl–Hirschman index based on suppliers' revenues, as described in Section 4.4. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Firm-level industry controls based on TNIC-3 industries are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers financial constraint indicator FC^{ind}_{50}. See Sections 2.1 and 2.2 for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Return		
	(1)	(2)	(3)
$FC^{sup}_{50} \times D^{ind}_1 \times HHI^{sup}$	-7.011^{**}		
	(3.040)		
$FC^{sup}_{50} \times D^{ind}_2 \times HHI^{sup}$		-5.896^{**}	
		(2.989)	
$FC^{sup}_{50} \times D^{ind}_3 \times HHI^{sup}$			-3.345
			(2.559)
Downturn–Quarter FE	Y	Y	Y
Firm FE	Y	Y	Y
Observations	167,490	167,490	167,490
Adjusted R^2	0.076	0.078	0.086

Table 8. Downstream Amplification: Real Effects on Balance Sheets. This table reports output from the estimation of β_2 in Equation (1). The sample consists of firm-quarter observations during the period 1996 to 2019. We estimate the specification on four dependent variables. In Panel A, the dependent variable is *Change in Sales by Assets*, the annual change in *Sales by Assets*—the ratio of sales (Compustat's `saleq`) to the lag of total assets (`atq`). In Panel B, the dependent variable is *Change in Costs by Assets*, the annual change in *Costs by Assets*—the ratio of costs of goods sold (`cogsq`) to lagged assets. In Panel C, the dependent variable is *Investment Change*, the annual change in *Investment*—the ratio of quarterly capital expenditures (`capxy`, adjusted to reflect quarterly values) to the quarterly lag of property, plant and equipment (`ppentq`). In Panel D, the dependent variable is *Change in Asset Sale*, the annual change in *Asset Sale*—the ratio of quarterly sale of property (`sppey`, adjusted to reflect quarterly values) to the lag of property, plant and equipment. All dependent variables are measured in percentage points. FC_{50}^{sup} is a firm-level indicator variable that equals one if FC^{sup} is in the top 50% of its yearly distribution, and zero otherwise. FC^{sup} is the fraction of suppliers with long-term debt largely due as predicted in the previous year, where suppliers are identified by VTNIC networks. See Section 2.2 for details on financial constraint measurements. D_1^{ind}, D_2^{ind}, and D_3^{ind} are firm-level industry downturn indicators of severe, medium, and mild downturns, respectively, based on TNIC-2 industries. See Section 2.3 for detailed definitions of downturn indicators. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Firm-level industry controls based on TNIC-3 industries are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers' financial constraint indicator FC_{50}^{ind}. Specifications include interactions of all control variables with D^{ind}. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Sales

	Change in Sales by Assets					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC_{50}^{sup} \times D_1^{ind}$	−0.291*	−0.351**				
	(0.160)	(0.155)				
$FC_{50}^{sup} \times D_2^{ind}$			−0.289**	−0.272**		
			(0.124)	(0.119)		
$FC_{50}^{sup} \times D_3^{ind}$					−0.317***	−0.278***
					(0.104)	(0.100)
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	166,877	166,877	166,877	166,877	166,877	166,877
Adjusted R^2	0.040	0.156	0.040	0.155	0.040	0.155

Panel B. Costs

	Change in Costs by Assets					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC_{50}^{sup} \times D_1^{ind}$	−0.452***	−0.363**				
	(0.155)	(0.150)				
$FC_{50}^{sup} \times D_2^{ind}$			−0.328***	−0.271**		
			(0.118)	(0.115)		
$FC_{50}^{sup} \times D_3^{ind}$					−0.361***	−0.288***
					(0.099)	(0.096)
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	164,591	164,591	164,591	164,591	164,591	164,591
Adjusted R^2	0.031	0.142	0.030	0.141	0.030	0.141

Table 8. Downstream Amplification: Real Effects on Balance Sheets (Continued)

Panel C. Investment

	Investment Change					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC_{50}^{sup} \times D_1^{ind}$	0.805***	0.777***				
	(0.251)	(0.244)				
$FC_{50}^{sup} \times D_2^{ind}$			0.578***	0.541***		
			(0.195)	(0.194)		
$FC_{50}^{sup} \times D_3^{ind}$					0.250	0.227
					(0.171)	(0.170)
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	165,600	165,600	165,600	165,600	165,600	165,600
Adjusted R^2	0.014	0.080	0.014	0.079	0.013	0.079

Panel D. Asset Sale

	Change in Asset Sale					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC_{50}^{sup} \times D_1^{ind}$	−0.045	−0.033				
	(0.061)	(0.064)				
$FC_{50}^{sup} \times D_2^{ind}$			−0.049	−0.045		
			(0.049)	(0.052)		
$FC_{50}^{sup} \times D_3^{ind}$					−0.035	−0.031
					(0.042)	(0.044)
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	123,783	123,783	123,783	123,783	123,783	123,783
Adjusted R^2	0.003	0.027	0.003	0.027	0.003	0.027

Table 9. Downstream Amplification: Real Effects on Product Prices and Quantities. This table reports output from the estimation of β_2 in a specification similar to Equation (1) at the product level. The sample consists of product-quarter observations during the period 2006 to 2019. A product corresponds to a unique UPC produced by firms in our baseline sample. We estimate the specification on three dependent variables. In columns (1)–(3), the dependent variable is *Revenue*—the natural log of the total dollar value of sales of a product across all U.S. retailers in the sample for a given quarter. In columns (4)–(6), the dependent variable is *Quantity*—the natural log of the number of units sold of a product in a given quarter. In columns (7)–(9), the dependent variable is *Price*—the natural log of the average price of a product in a given quarter. The coefficients reported correspond to $100(e^{\beta} - 1)$ where β is the coefficient of the original regressions with logged dependent variables. See Section 5.2 for variable definitions and details of the product-level sample construction. FC_{50}^{sup} is a firm-level indicator variable that equals one if FC^{sup} is in the top 50% of its yearly distribution, and zero otherwise. FC_{33}^{sup} equals one if FC^{sup} is in the top tercile of its yearly distribution, zero if bottom tercile, and is missing otherwise. FC^{sup} is the fraction of suppliers with long-term debt largely due as predicted in the previous year, where suppliers are identified by VTNIC networks. See Section 2.2 for details on financial constraint measurements. D_1^{ind}, D_2^{ind}, and D_3^{ind} are firm-level industry downturn indicators of severe, medium, and mild downturns, respectively, based on TNIC-2 industries. See Section 2.3 for detailed definitions of downturn indicators. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Firm-level industry controls based on TNIC-3 industries are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers financial constraint indicator FC_{50}^{ind}. See Sections 2.1 and 2.2 for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable:								
	Revenue			Quantity			Price		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$FC_{50}^{sup} \times D_1^{ind}$	-26.772^{**}			-30.943^{***}			6.040^{**}		
	(12.790)			(10.941)			(2.520)		
$FC_{50}^{sup} \times D_2^{ind}$		-19.272^{**}			-23.190^{***}			5.100^{***}	
		(8.698)			(7.576)			(1.383)	
$FC_{50}^{sup} \times D_3^{ind}$			-25.984^{***}			-25.873^{***}			-0.150
			(8.932)			(8.015)			(1.678)
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,753,475	1,753,475	1,753,475	1,753,475	1,753,475	1,753,475	1,753,475	1,753,475	1,753,475
Adjusted R^2	0.689	0.690	0.691	0.688	0.689	0.690	0.830	0.831	0.831

Table 10. Real Effects on Product Prices and Quantities by Existing Inventory. This table reports output from the estimation of the triple interaction coefficient from a triple differences specification where we interact FC_{50}^{sup}, D^{ind}, and *Invent*. The sample consists of product-quarter observations during the period 2006 to 2019. A product corresponds to a unique UPC produced by firms in our baseline sample. We estimate the specification on three dependent variables. In columns (1)–(3), the dependent variable is *Revenue*—the natural log of the total dollar value of sales of a product across all U.S. retailers in the sample for a given quarter. In columns (4)–(6), the dependent variable is *Quantity*—the natural log of the number of units sold of a product in a given quarter. In columns (7)–(9), the dependent variable is *Price*—the natural log of the average price of a product in a given quarter. The coefficients reported correspond to $100(e^{\beta} - 1)$ where β is the coefficient of the original regressions with logged dependent variables. See Section 5.2 for variable definitions and details of the product-level sample construction. FC_{50}^{sup} is a firm-level indicator variable that equals one if FC^{sup} is in the top 50% of its yearly distribution, and zero otherwise. FC_{33}^{sup} equals one if FC^{sup} is in the top tercile of its yearly distribution, zero if bottom tercile, and is missing otherwise. FC^{sup} is the fraction of suppliers with long-term debt largely due as predicted in the previous year, where suppliers are identified by VTNIC networks. See Section 2.2 for details on financial constraint measurements. D_1^{ind}, D_2^{ind}, and D_3^{ind} are firm-level industry downturn indicators of severe, medium, and mild downturns, respectively, based on TNIC-2 industries. See Section 2.3 for detailed definitions of downturn indicators. *Invent* is the lag of the ratio of quarterly inventories (Compustat's `inventq`) to lagged total assets (`atq`), in percentage points. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Firm-level industry controls based on TNIC-3 industries are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers financial constraint indicator FC_{50}^{ind}. See Sections 2.1 and 2.2 for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable:								
	Revenue			Quantity			Price		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$FC_{50}^{sup} \times D_1^{ind} \times Invent$	0.438			0.713*			−0.273***		
	(0.435)			(0.394)			(0.084)		
$FC_{50}^{sup} \times D_2^{ind} \times Invent$		0.685*			0.746**			−0.060	
		(0.389)			(0.356)			(0.047)	
$FC_{50}^{sup} \times D_3^{ind} \times Invent$			0.668**			0.675***			−0.007
			(0.277)			(0.248)			(0.042)
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,732,326	1,732,326	1,732,326	1,732,326	1,732,326	1,732,326	1,732,326	1,732,326	1,732,326
Adjusted R^2	0.690	0.691	0.692	0.689	0.690	0.691	0.832	0.832	0.832

Appendix A Robustness

A.1 Longer Period of Debt Maturity

Studies that use long-term debt maturity as an identification strategy face concerns about the endogeneity of firms' debt structures. In our framework, the causal interpretation of the amplification effects requires ensuring that results do not reflect omitted variables that simultaneously explain both upstream debt structure and industry downturn severity. Specifically, a potential issue is whether firms adjust their long-term debt structure in anticipation of incoming shocks. In Almeida et al. (2012), this could reflect variation in corporate managerial quality, which could also explain differences in performance across firms during downturns. In Carvalho (2015), cross-sectional variation in industries' debt maturity could capture persistent differences or secular trends in industries' debt structures. The authors thoroughly address these concerns to ensure the causal interpretation of their results.

In our framework, such endogeneity concerns are alleviated by two considerations. First, the analysis links firms' economic distress to suppliers' financial distress, which requires potential sources of bias to systematically predict both suppliers' debt structures and shocks to customer industries. Second, our firm-level fixed effects absorb any time-invariant, unobserved firm characteristics, including persistent differences in suppliers' long-term debt structures.

Nonetheless, to account for possible debt maturity adjustments in response to anticipated customer downturns, we perform additional robustness checks proposed in the literature. We re-estimate our baseline regressions using long-term debt maturity predicted in longer time windows. The underlying reasoning is that managers are less likely to anticipate economic shocks multiple years in advance and adjust debt structures accordingly.

The ratio of Compustat variables `dd3` to (`dd1 + dltt`) is the fraction of total long-term debt due in three years. Thus, the three-year lag of this ratio is the share of long-term debt maturing in a given year as predicted three years before. As in our benchmark analysis, we classify firms in the top tercile of the yearly distributions of these shares as financially constrained ($FC^f = 1$). We then use FC^f to construct FC^{ind} and FC^{sup}, our indicators of industry and supplier high-debt maturity, respectively, following the same procedure described in Section 2.2. Finally, we estimate Equation (1) using this new set of financing constraint indicators.

While debt maturity predicted over longer time windows is naturally less accurate, it addresses issues related to managers' anticipation. In this framework, unobserved confounders that threaten the causal interpretation of our results must be correlated with both contemporaneous downturns in firms' industries and their suppliers' debt structure *as of three years prior*. Table A.1 reports the results.

— PLACE TABLE A.1 ABOUT HERE —

Across all specifications, the results show that firms suffer larger valuation losses during downturns if their suppliers have long-term debt largely due, consistent with our baseline results. While the magnitudes and statistical significance of the point estimates are lower than those reported in Table 2, reflecting the reduced accuracy in predicting debt maturity multiple years in advance, the estimated effects are economically sizable. From our specifications with firm fixed effects, the estimates indicate that firms in the top 50% of the distribution of the fraction of constrained suppliers experience 0.80–0.98 p.p. lower abnormal returns during downturns, which corresponds to 8.5-11.2% larger valuation losses. Comparing firms in the top and bottom terciles of this distribution, the results show an additional 1.07 to 1.30 p.p. lower abnormal returns, which implies an amplification of negative shocks of 12.1 to 17.8%.

A.2 Industry-Level Vertical Relationships

A potential concern with our baseline analysis is that the VTNIC measures potential vertical relatedness rather than actual transaction flows between firms. To ensure robustness across different network specifications, this exercise examines whether results hold using conventional industry-level measures based on fixed classifications. In this exercise, we rely on the conventional approach of constructing industry-level measures of financial constraints using fixed industry classifications, as in Carvalho (2015) and Garcia-Appendini (2018). To connect industries in supplier-customer relationships, we leverage the BEA input-output matrices as in Becker and Thomas (2011) and Almeida et al. (2017, 2019).

Variable Construction. NAICS industries are matched to Detail-level industries in the BEA benchmark tables using NAICS–BEA concordance files. We compute $FC^{ind}_{j,t}$, the share of high long-term debt maturity firms (i.e., the average of FC^{f}) in Detail industry j at quarter t. This is the same procedure used with TNIC networks in Section 2.2, but computed at the industry-year level. Again, we construct an indicator FC_{50}^{ind} that equals one if FC^{ind} is in the top 50% of its yearly distribution.

Next, we use FC^{ind} and IO tables to construct an industry-level measure of long-term debt maturity across upstream industries. We use the BEA's benchmark industry-by-industry total requirements matrices, where entry (j,k) denotes the dollar value of production required—directly and indirectly—by industry k for industry j to deliver one dollar of output.

We combine our industry debt maturity variables and IO tables as follows. For Detail-level industry j at year t, we compute:

$$FC_{j,t}^{sup} = \sum_{k=1}^{K} \mathbf{M}_{j,k,t'} \cdot FC_{k,t}^{ind}, \tag{3}$$

where $\mathbf{M}_{j,k,t'}$ is the element j,k of the IO matrix published at year $t^{'}$. The resulting value proxies for financial constraints across supplier industries of industry j based on vertical connectedness to upstream industries and the respective fraction of constrained firms. K is the total number of industries in matrix $\mathbf{M}$, and $t^{'}$ is the publication year closest to t. Since benchmark IO matrices are published every five years, the 1997 matrix is used for quarters in 1996–1999, the 2002 matrix for quarters in 2000–2004, and so on.

Similar to our main exercise, we create indicator variables based on quantiles of the continuous variable $FC_{j,t}^{sup}$. Specifically, $FC_{50\,j,t}^{sup}$ is a binary variable that equals one if $FC_{j,t}^{sup}$ is above its yearly median value, and $FC_{33\,j,t}^{sup}$ equals one if $FC^{sup}{}_{j,t}$ is above its distribution's top tercile, zero if bottom tercile, and missing otherwise.

In the procedure described, $FC_{j,t}^{sup}$ is constructed by aggregating long-term debt maturity values across suppliers, thus being an intensity measure. However, the relevant measure should capture whether each upstream industry is financially constrained. For instance, a scenario in which two suppliers have 20% of their long-term debt due is different from one in which one supplier has 10%, and the other has 30% if the financing constraint binds at 25%. To address such concerns, we consider the following alternative measure:

$$FC_{j,t}^{sup} = \sum_{k=1}^{K} \mathbf{M}_{j,k,t'} \cdot FC_{50\,k,t}^{ind}, \tag{4}$$

which uses our industry high debt maturity indicator FC_{50}^{ind} to construct an industry-level measure of suppliers' constraints. In this context, $FC_{j,t}^{sup}$ measures the dollar value of output required from financially constrained supplier industries per dollar of output delivered by industry j. From this continuous variable, we construct the usual quantile indicators.

Specification and Results. We replicate our main exercise by estimating:

$$\begin{aligned} AbnRet_{i,j,t} = {} & \alpha_0 \cdot FC_{i,t}^{f} + \alpha_1 \cdot FC_{j,t}^{ind} + \alpha_2 \cdot FC_{j,t}^{sup} \\ & + \beta_0 \cdot \left[FC_{i,t}^{f} \times D_{j,t}^{ind} \right] + \beta_1 \cdot \left[FC_{j,t}^{ind} \times D_{j,t}^{ind} \right] + \beta_2 \cdot \left[FC_{j,t}^{sup} \times D_{j,t}^{ind} \right] \\ & + \delta_0' \cdot X_{i,j,t} + \delta_1' \cdot \left[X_{i,j,t} \times D_{j,t}^{ind} \right] + \sum_i \mu_i + \sum_j \sum_t [\mu_t \times D_{j,t}^{ind}] + \epsilon_{i,j,t}, \end{aligned} \tag{5}$$

where i, j and t specify firm, industry, and quarter, respectively. Equation (5) is similar to Equation (1), but with all variables relative to industries constructed at the industry level. These variables are defined at BEA's Detail-level sectors, except for the downturn indicators, which are defined at the broader Summary level (cf. Section 2.3).[22] To the extent that this approach relies on a lower frequency of industry variables and arguably reduced accuracy in vertical linkages, verifying that our results hold in this framework serves as validation. Estimates of β_2 in Equation (5) are reported in Table A.2.

— PLACE TABLE A.2 ABOUT HERE —

Based on our specifications with firm fixed effects reported in Panel A, we find that firms in the top 50% of FC^{sup} as described in Equation (3) experience 1.01 to 1.85 p.p. lower abnormal returns during downturns, relative to firms in the bottom 50% of this distribution. These point estimates are slightly larger than those of our main exercise and translate into much larger amplification effects. The reason is that the estimated total effects of downturns based on fixed industries are smaller than those based on the TNIC-2. This could partially reflect the fact that TNIC networks capture firms' horizontal relations more precisely than fixed industry classifications (Frésard et al., 2020).

In Panel A, the reported valuation losses translate into an amplification of industry negative shocks between 19.0% and 42.2%. These figures are even larger in Panel B, where we compare firms in the top

[22] For expositional ease, we use the same subscript j to denote different industry levels in Equation (5).

and bottom terciles of the distribution of $FC_{j,t}^{sup}$. Including firm-specific effects, additional valuation losses during downturns range from 2.74 to 3.31 p.p. lower in abnormal returns, corresponding to an amplification effect of 49.5%–70.7%. While these findings suggest that our results are robust to different methods for measuring networks and downturns, the figures in Table A.2 should be interpreted cautiously, in favor of the more conservative estimates in our baseline approach.

In addition to results based on the quantile dummy variables, we also report the results from regressions based on continuous variation of FC^{sup} as defined in Equation (3) in Table C.2. Including firm fixed effects, the estimates of β_2 imply that an increase of one standard deviation in FC^{sup} is associated with 0.51 to 0.91 lower abnormal returns, depending on the classification of downturn. Finally, we also report results of the estimation of β_2 in Equation (5) using the alternative measure of FC^{sup} described in Equation (4). Table C.3 reports results based on the indicator variable approach to measure suppliers' financing constraints, and Table C.4 reports results based on the continuous variation of FC^{sup}. Overall, our main results are robust to using substantially different methods of measuring suppliers' financing constraints and fixed industry classifications from IO tables.

Table A.1. Downstream Amplification of Downturns with Financing Constraints Predicted by Long-term Debt Maturity Three Years in Advance. This table reports output from the estimation of β_2 in Equation (1). The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), in percentage points. FC^{sup}_{50} is a firm-level indicator variable that equals one if FC^{sup} is in the top 50% of its yearly distribution. FC^{sup}_{33} equals one if FC^{sup} is in the top tercile of its yearly distribution, zero if bottom tercile, and is missing otherwise. FC^{sup} is the fraction of suppliers with long-term debt largely due as predicted three years in advance, where suppliers are identified by VTNIC networks. See Section 2.2 and Section A.1 for details on financial constraint measurements. D^{ind}_1, D^{ind}_2, and D^{ind}_3 are firm-level industry downturn indicators of severe, medium, and mild downturns, respectively, based on TNIC-2 industries. See Section 2.3 for detailed definitions of downturn indicators. Panels A and B report additional valuation losses during the industry downturn specified in the row when FC^{sup}_{50} and FC^{sup}_{33} equal one, respectively. Amplification (%) reports the amplification of the downturn implied by the respective point estimate. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f predicted three years in advance. Firm-level industry controls based on TNIC-3 industries are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers' financial constraint indicator FC^{ind}_{50} predicted three years in advance. See Sections 2.1 and 2.2 for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Top *vs.* Bottom 50% Supplier Financing Constraints

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC^{sup}_{50} \times D^{ind}_1$	-1.105^{**}	-0.953^{*}				
	(0.511)	(0.516)				
$FC^{sup}_{50} \times D^{ind}_2$			-0.989^{**}	-0.800^{*}		
			(0.414)	(0.416)		
$FC^{sup}_{50} \times D^{ind}_3$					-0.736^{**}	-0.979^{***}
					(0.359)	(0.359)
Amplification (%)	13.8	11.2	10.7	8.5	7.1	9.6
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	120,792	120,792	120,792	120,792	120,792	120,792
Adjusted R^2	0.032	0.069	0.039	0.076	0.049	0.085

Panel B. Top *vs.* Bottom 33% Supplier Financing Constraints

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC^{sup}_{33} \times D^{ind}_1$	-1.601^{***}	-1.303^{**}				
	(0.611)	(0.618)				
$FC^{sup}_{33} \times D^{ind}_2$			-1.420^{***}	-1.067^{**}		
			(0.482)	(0.488)		
$FC^{sup}_{33} \times D^{ind}_3$					-0.952^{**}	-1.204^{**}
					(0.479)	(0.486)
Amplification (%)	21.9	17.8	17.2	12.6	9.2	12.1
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	100,969	100,969	100,969	100,969	100,969	100,969
Adjusted R^2	0.036	0.078	0.041	0.084	0.050	0.095

Table A.2. Downstream Amplification of Downturns via the Supplier Financing Constraint Channel: Input-Output Analysis. This table reports output from the estimation of β_2 in Equation (5). The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), in percentage points. FC_{50}^{sup} is an indicator that equals one if FC^{sup} is in the top 50% of its yearly distribution, and zero otherwise. FC_{33}^{sup} equals one if FC^{sup} is in the top tercile of its yearly distribution, zero if bottom tercile, and is missing otherwise. FC^{sup} is an industry-level measure of the intensity of long-term debt maturing across supplier industries as predicted in the previous year. D_1^{ind}, D_2^{ind}, and D_3^{ind} are industry-level downturn indicators of severe, medium, and mild downturns, respectively. Industry-level variables are constructed following the BEA IO tables classification. Financing constraint indicators and industry controls are at the Detail industry level, whereas downturn indicators are at the broader Summary industry level. See Section 2.3 for detailed definitions of downturn indicators. Panels A and B report additional valuation losses during the industry downturn specified by the row when FC_{50}^{sup} and FC_{33}^{sup} equal one, respectively. Amplification (%) reports the amplification of the downturn implied by the respective point estimate. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Industry controls are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers' financial constraint indicator FC_{50}^{ind}. See Sections 2.1, 2.2, and A.2 for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Top *vs.* Bottom 50% Supplier Financing Constraints

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC_{50}^{sup} \times D_1^{ind}$	-1.877^{***}	-1.845^{***}				
	(0.567)	(0.575)				
$FC_{50}^{sup} \times D_2^{ind}$			-1.279^{***}	-1.289^{***}		
			(0.447)	(0.453)		
$FC_{50}^{sup} \times D_3^{ind}$					-0.918^{**}	-1.014^{**}
					(0.394)	(0.398)
Amplification (%)	43.5	42.2	26.0	27.3	15.9	19.00
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	200,373	200,373	200,373	200,373	200,373	200,373
Adjusted R^2	0.027	0.065	0.029	0.067	0.031	0.069

Panel B. Top *vs.* Bottom 33% Supplier Financing Constraints

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC_{33}^{sup} \times D_1^{ind}$	-2.428^{***}	-2.848^{***}				
	(0.804)	(0.826)				
$FC_{33}^{sup} \times D_2^{ind}$			-3.087^{***}	-3.307^{***}		
			(0.627)	(0.641)		
$FC_{33}^{sup} \times D_3^{ind}$					-2.791^{***}	-2.736^{***}
					(0.570)	(0.579)
Amplification (%)	47.2	57.2	61.7	70.7	47.4	49.5
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	130,945	130,945	130,945	130,945	130,945	130,945
Adjusted R^2	0.030	0.075	0.032	0.077	0.034	0.079

Appendix B Alternative Measures of Network-Based Financing Constraints

This appendix replicates the main results using alternative measures of industry peers' and suppliers' financing constraints that incorporate pairwise similarity scores from the TNIC and VTNIC databases. As described in Section 2, these scores measure the degree of potential horizontal and vertical proximity between pairs of firms. Unlike binary classifications, these measures capture both the extensive margin (whether firms are connected) and the intensive margin (the strength of these relationships).

To capture the degree of industry peers' financing constraints, we compute

$$FCS_{i,t}^{ind} = \sum_{k \in I(i,t)} H_{i,k,t} \cdot FC_{k,t}^{f} \tag{6}$$

where $H_{i,k,t}$ is the horizontal score between firms i and k at year t, and $I(i,t)$ is the set of industry peers of firm i at year t, as per TNIC-3 industries. Therefore, $FCS_{i,t}^{ind}$ is the sum of horizontal scores between firm i and its *constrained* product market peers, as measured by FC^f. Similarly, the degree of firm i's suppliers' financing constraints is measured by computing

$$FCS_{i,t}^{sup} = \sum_{k \in S(i,t)} V_{i,k,t} \cdot FC_{k,t}^{f} \tag{7}$$

where $V_{i,k,t}$ is the vertical score between firms i and k at year t—which measures the likelihood of firm k being upstream relative to i—and $S(i,t)$ is the set of suppliers of firm i at year t as per VTNIC networks. $FCS_{i,t}^{sup}$ is the sum of vertical scores between firm i and its *constrained* suppliers. We estimate a specification similar to Equation (1), replacing $FC_{i,t}^{ind}$ and $FC_{i,t}^{sup}$ with $FCS_{i,t}^{ind}$ and $FCS_{i,t}^{sup}$, respectively. We construct the usual quantile indicator variables FCS_{50}^{sup} and FCS_{33}^{sup}. In addition, we estimate a specification with the continuous variable FCS^{sup} scaled by its standard deviation to facilitate the interpretation of coefficients. As in Equation (1), the coefficient of interest is β_2, which captures differential impacts of downturns when a firm's suppliers are constrained according to our measures based on vertical scores.

Tables B.1 and B.2 report the results of this exercise. The estimates of β_2 are negative and significant across all specifications. Table B.1 reports results using quantile indicator variables. Panel

A shows that firms with above-median vertical scores to constrained suppliers experience 0.86-1.87 p.p. lower abnormal returns during downturns, corresponding to amplification effects of 8.8% to 25.5%. The estimated effects for the top and bottom terciles of this distribution range from 1.02 to 2.15 p.p. lower abnormal returns during negative shocks, as reported in Panel B. These values translate into 11.8% to 29.7% amplification of downturns.

Table B.2 reports results for the continuous measure of vertical scores among upstream-constrained firms. Estimates indicate that a one-standard-deviation increase in this variable is associated with 0.46 to 0.97 p.p. lower returns during downturns, depending on the severity of the negative shock. These results confirm that the baseline findings are robust across alternative measures that capture both the extensive and intensive margins of upstream financing constraints, further validating the downstream amplification mechanism.

Table B.1. Downstream Amplification of Downturns via the Supplier Financing Constraint Channel. Vertical Scores. This table reports output from the estimation of β_2 in Equation (1). The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), in percentage points. FCS_{50}^{sup} is a firm-level indicator variable that equals one if FCS^{sup} is in the top 50% of its yearly distribution, and zero otherwise. FCS_{33}^{sup} equals one if FCS^{sup} is in the top tercile of its yearly distribution, zero if bottom tercile, and is missing otherwise. FCS^{sup} is the sum of the vertical scores of a firm's upstream financially constrained suppliers according to long-term debt largely due as predicted in the previous year, where suppliers are identified by VTNIC networks. See Section B for details on financial constraint measurements. D_1^{ind}, D_2^{ind}, and D_3^{ind} are firm-level industry downturn indicators of severe, medium, and mild downturns, respectively, based on TNIC-2 industries. See Section 2.3 for detailed definitions of downturn indicators. Panels A and B report additional valuation losses during the industry downturn specified by the row when FC_{50}^{sup} and FC_{33}^{sup} equal one, respectively. Amplification (%) reports the amplification of the downturn implied by the respective point estimate. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Firm-level industry controls based on TNIC-3 industries are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers' financial constraint indicator FC_{50}^{ind}, based on horizontal scores. See Section 2.1 and Appendix B for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Top *vs.* Bottom 50% Supplier Financing Constraints

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FCS_{50}^{sup} \times D_1^{ind}$	-1.866^{***}	-1.571^{***}				
	(0.488)	(0.503)				
$FCS_{50}^{sup} \times D_2^{ind}$			-1.189^{***}	-0.982^{**}		
			(0.391)	(0.398)		
$FCS_{50}^{sup} \times D_3^{ind}$					-1.029^{***}	-0.858^{**}
					(0.343)	(0.346)
Amplification (%)	25.5	20.9	14.2	11.7	10.6	8.8
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	169,248	169,248	169,248	169,248	169,248	169,248
Adjusted R^2	0.037	0.071	0.043	0.078	0.051	0.086

Panel B. Top *vs.* Bottom 33% Supplier Financing Constraints

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FCS_{33}^{sup} \times D_1^{ind}$	-2.146^{***}	-1.444^{**}				
	(0.608)	(0.630)				
$FCS_{33}^{sup} \times D_2^{ind}$			-1.368^{***}	-1.022^{**}		
			(0.496)	(0.508)		
$FCS_{33}^{sup} \times D_3^{ind}$					-1.218^{***}	-1.157^{***}
					(0.441)	(0.447)
Amplification (%)	29.7	17.9	16.7	12.0	12.5	11.8
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	111,150	111,150	111,150	111,150	111,150	111,150
Adjusted R^2	0.039	0.080	0.045	0.086	0.053	0.095

Table B.2. Downstream Amplification of Downturns via the Supplier Financing Constraint Channel: Continuous Measure of Vertical Scores. This table reports output from the estimation of β_2 in Equation (1) with continuous measures of vertical and horizontal financial constraints based on pairwise scores. The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), in percentage points. FCS^{sup} is the sum of the vertical scores of a firm's upstream financially constrained suppliers according to long-term debt largely due as predicted in the previous year, where suppliers are identified by VTNIC networks. See Section B for for details on financial constraint measurements. D_1^{ind}, D_2^{ind}, and D_3^{ind} are firm-level industry downturn indicators of severe, medium, and mild downturns, respectively, based on TNIC-2 industries. See Section 2.3 for detailed definitions of downturn indicators. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Firm-level industry controls based on TNIC-3 industries are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers financial constraint indicator FC_{50}^{ind}, based on horizontal scores. See Section 2.1 and Appendix B for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FCS^{sup} \times D_1^{ind}$	-0.954^{***}	-0.895^{***}				
	(0.197)	(0.203)				
$FCS^{sup} \times D_2^{ind}$			-0.701^{***}	-0.628^{***}		
			(0.163)	(0.167)		
$FCS^{sup} \times D_3^{ind}$					-0.572^{***}	-0.551^{***}
					(0.148)	(0.150)
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	169,248	169,248	169,248	169,248	169,248	169,248
Adjusted R^2	0.037	0.071	0.043	0.078	0.051	0.086

Appendix C Additional Results

Table C.1. Downstream Amplification of Downturns via the Supplier Financing Constraint Channel: Continuous Measure. This table reports output from the estimation of β_2 in Equation (1) with continuous measures of horizontal and vertical financial constraints. The sample consists of firm-quarter observations during the period 1996 to 2019. The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), measured in percentage points. FC^{sup} is the fraction of suppliers with long-term debt largely due as predicted in the previous year, where suppliers are identified by VTNIC networks. See Section 2.2 for details on financial constraint measurements. D_1^{ind}, D_2^{ind}, and D_3^{ind} are firm-level industry downturn indicators of severe, medium, and mild downturns, respectively, based on TNIC-2 industries. See Section 2.3 for detailed definitions of downturn indicators. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Firm-level industry controls based on TNIC-3 industries are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers financial constraint indicator FC_{50}^{ind}. See Sections 2.1 and 2.2 for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC^{sup} \times D_1^{ind}$	-5.413^*	-5.683^*				
	(3.054)	(3.090)				
$FC^{sup} \times D_2^{ind}$			-6.187^{***}	-7.255^{***}		
			(2.368)	(2.439)		
$FC^{sup} \times D_3^{ind}$					-6.751^{***}	-8.008^{***}
					(2.001)	(2.043)
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	167,490	167,490	167,490	167,490	167,490	167,490
Adjusted R^2	0.036	0.072	0.043	0.078	0.051	0.086

Table C.2. Downstream Amplification of Downturns via the Supplier Financing Constraint Channel: Input-Output Analysis with Continuous Measure. This table reports output from the estimation of β_2 in Equation (5). The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), in percentage points. FC^{sup} is an industry-level measure of intensity of long-term debt maturing across supplier industries as predicted in the previous year. D_1^{ind}, D_2^{ind}, and D_3^{ind} are industry-level downturn indicators of severe, medium, and mild downturns, respectively. Industry-level variables are constructed following the BEA IO tables classification. Financing constraint indicators and industry controls are at the Detail industry level, whereas downturn indicators are at the broader Summary industry level. See Section 2.3 for detailed definitions of downturn indicators. Firm controls are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Industry controls are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers financial constraint indicator FC_{50}^{ind}. See Sections 2.1, 2.2, and A.2 for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC^{sup} \times D_1^{ind}$	-1.739^{***}	-1.476^{***}				
	(0.546)	(0.555)				
$FC^{sup} \times D_2^{ind}$			-2.453^{***}	-2.148^{***}		
			(0.440)	(0.447)		
$FC^{sup} \times D_3^{ind}$					-2.183^{***}	-1.916^{***}
					(0.409)	(0.412)
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	200,373	200,373	200,373	200,373	200,373	200,373
Adjusted R^2	0.027	0.065	0.029	0.067	0.032	0.069

Table C.3. Downstream Amplification of Downturns via the Supplier Financing Constraint Channel: Input-Output Analysis with Alternative Measure. This table reports output from the estimation of β_2 in Equation (5). The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), in percentage points. FC_{50}^{sup} is an indicator that equals one if FC^{sup} is in the top 50% of its yearly distribution. FC_{33}^{sup} equals one if FC^{sup} is in the top tercile of its yearly distribution, zero if bottom tercile, and is missing otherwise. FC^{sup} is defined in Equation (4) and is the dollar value that high debt maturity supplier industries must produce for the client industry to deliver one dollar worth of output. D_1^{ind}, D_2^{ind}, and D_3^{ind} are industry-level downturn indicators of severe, medium, and mild downturns, respectively. Industry-level variables are constructed following the BEA IO tables classification. Financing constraint indicators and industry controls are at the Detail industry level, and downturn indicators are at the broader Summary industry level. See Section 2.3 for detailed definitions of downturn indicators. Panels A and B report additional valuation losses during the industry downturn specified by the row when FC_{50}^{sup} and FC_{33}^{sup} equal one, respectively. Amplification (%) reports the amplification of the downturn implied by the respective point estimate. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Industry controls are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers' financial constraint indicator FC_{50}^{ind}. See Sections 2.1 and A.2 for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Top *vs.* Bottom 50% Supplier Financing Constraints

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC_{50}^{sup} \times D_1^{ind}$	−0.584	−1.256**				
	(0.625)	(0.638)				
$FC_{50}^{sup} \times D_2^{ind}$			−1.273***	−1.305***		
			(0.489)	(0.498)		
$FC_{50}^{sup} \times D_3^{ind}$					−0.875**	−0.671
					(0.433)	(0.439)
Amplification	11.8	26.9	26.1	28.4	15.1	12.3
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	200,373	200,373	200,364	200,364	200,364	200,364
Adjusted R^2	0.027	0.065	0.030	0.067	0.032	0.069

Panel B. Top *vs.* Bottom 33% Supplier Financing Constraints

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC_{33}^{sup} \times D_1^{ind}$	−3.160***	−3.319***				
	(0.861)	(0.876)				
$FC_{33}^{sup} \times D_2^{ind}$			−2.910***	−2.702***		
			(0.681)	(0.699)		
$FC_{33}^{sup} \times D_3^{ind}$					−2.502***	−2.205***
					(0.606)	(0.615)
Amplification	66.4	70.7	55.9	54.2	41.7	38.4
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	134,722	134,722	134,722	134,722	134,722	134,722
Adjusted R^2	0.029	0.067	0.032	0.070	0.035	0.072

Table C.4. Downstream Amplification of Downturns via the Supplier Financing Constraint Channel: Input-Output Analysis with Continuous Alternative Measure. This table reports output from the estimation of β_2 in Equation (5). The dependent variable is *Abnormal Return*, the quarterly stock return minus that of a portfolio matched by size, book-to-market and previous quarter returns as in Daniel et al. (1997), in percentage points. FC^{sup} is defined in Equation (4) and is the dollar value that high debt maturity supplier industries must produce for the client industry to deliver one dollar worth of output. D_1^{ind}, D_2^{ind}, and D_3^{ind} are industry-level downturn indicators of severe, medium, and mild downturns, respectively. Industry-level variables are constructed following the BEA IO tables classification. Financing constraint indicators and industry controls are at the Detail industry level and downturn indicators are at the broader Summary industry level. See Section 2.3 for detailed definitions of downturn indicators. Firm control variables are *Q*, *Cash Flow*, *Cash*, *Size*, *Rated*, *Investment Grade*, *Leverage*, *Tangibility*, and the firm's own financial constraint indicator FC^f. Industry controls are *Industry Leverage*, *HHI*, *Asset Maturity*, one, two, and three lags of *Industry Revenue Growth*, and the firm's industry peers financial constraint indicator FC_{50}^{ind}. See Sections 2.1, and A.2 for variable definitions. Specifications include interactions of all control variables with the corresponding industry downturn indicator. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Return					
	(1)	(2)	(3)	(4)	(5)	(6)
$FC^{sup} \times D_1^{ind}$	-0.778^{**}	-0.588^{*}				
	(0.315)	(0.320)				
$FC^{sup} \times D_2^{ind}$			-1.249^{***}	-1.042^{***}		
			(0.259)	(0.262)		
$FC^{sup} \times D_3^{ind}$					-1.017^{***}	-0.869^{***}
					(0.231)	(0.232)
Downturn–Quarter FE	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y
Observations	200,373	200,373	200,373	200,373	200,373	200,373
Adjusted R^2	0.027	0.065	0.030	0.067	0.032	0.069