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Financial Heterogeneity, Investment, and Firm Interactions

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ABSTRACT: Recent literature has shown that corporate indebtedness affects firm-level investment behavior but not necessarily aggregate business cycles. I argue that interactions among heterogeneous firms play an important role in equilibrium. After a downturn, financially unconstrained firms in financially constrained industries significantly increase capital ex-penditure to substitute depressed investment by their financially constrained competitors. The increase in investment, primarily driven by small and medium firms, leads to substantial gains in future sales. Using a new empirical approach, I further show that equilibrium effects are unambiguously countercyclical because the increase in investment by unconstrained firms does not crowd out investment by financially constrained competitors. The "competitive interaction channel" underscored in this paper may play an important role in mitigating the impact of negative shocks in macroeconomic models with financial heterogeneity.

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WORKING PAPERS

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1 Introduction

Corporate debt has attracted increasing attention since the pandemic. With record-high corporate leverage in both the United States and abroad, the macroeconomic implications of corporate indebtedness are now at the center of both academic and policy debates (Brunnermeier and Krishnamurthy, 2020). In this paper I document new empirical facts about how product market competitors respond to one another's financial constraints over the cycle through the investment channel. When a downturn hits, financially constrained firms have to forgo investment opportunities because of tightening financial constraints, a situation that, *ceteris paribus*, encourages financially unconstrained competitors to significantly increase investment relative to financially unconstrained firms with no financially constrained competitors. More importantly, I demonstrate that equilibrium effects of such firm interactions are unambiguously countercyclical because the increase in investment does not *further* reduce investment by constrained competitors.

My empirical analysis focuses on the triple interaction between a firm's own financial constraints, its competitors' financial constraints, and shocks. To measure shocks, I extend the decomposition method in di Giovanni, Levchenko, and Mejean (2014) to separate industry upturns and downturns as well as idiosyncratic residuals. The triple interaction, therefore, captures how investment correlates with a firm's own and its competitors' financial constraints over the cycle. Yet making a causal interpretation of the triple interaction is not straight forward. Why would financially unconstrained firms relatively increase investment in the presence of financially constrained competitors during downturns? One interpretation is that unconstrained firms increase investment to substitute depressed investment by constrained competitors. I refer to this interpretation as the "competitive interaction channel." Alternatively, unconstrained firms may proactively increase investment to crowd out investment by constrained competitors. I call this the "crowding-out channel". The two channels would provide exactly the same coefficient on the triple interaction.

The problem of how to interpret the triple interaction is critical because the two channels lead to different equilibrium implications for aggregate investment and the business cycle. Under the competitive interaction channel, firm interactions partially offset depressed investment by financially constrained firms and, therefore, mitigate aggregate fluctuations. Under the crowding-out channel, on the other hand, equilibrium effects are ambiguous because financially constrained firms are simultaneously deterred from investing when unconstrained firms increase investment. In a slightly different setting, Khanna and Tice (2005) show that in cities with both high-and low-leverage retailers, the latter strategically lower prices during recessions to force high-leverage retailers to exit, and high-efficiency retailers with high debt are particularly vulnerable. Competition plays a disruptive role and likely lowers industrywide efficiency in this particular case. Likewise, if the crowding-out channel prevails, financially unconstrained firms may choose to intensify competition by investing in products close to those of their competitors so that financially constrained competitors will give up future investment as they expect lower future returns due to increased competition. This channel, also called the deterrence effect (Dixit, 1980, Smiley, 1988), leads to ambiguous net effects on investment in the short run and may increase concentration in the medium run. Unfortunately, a systematic and theoretically coherent approach separating between different channels is still lacking in the literature. For instance, earlier studies on similar topics, such as those by Rauh (2006) and Grieser and Liu (2019), mitigate the causality concern by only qualitatively examining some specific events.

In this paper I offer a simple model with empirically testable predictions to distinguish between different channels driving the interaction between firms' own financial constraints, those of its competitors, and business cycles. Following Ottonello and Winberry (2020), I conceptualize a firm's investment decision as a function of its own financial constraints and expected returns of investment projects. I further introduce nonconvex adjustment costs following the literature on firm investment (Doms and Dunne, 1998, Cooper and Haltiwanger, 2006). If competitors in the same industry increase (reduce) investment, doing so will lower (raise) industry-wide expected returns. The competitive interaction channel is easily explained by this model. When financial constraints tighten during a downturn, financially constrained firms lose access to credit and have to forgo high-return investment projects. *Ceteris paribus*, this situation induces unconstrained competitors to increase investment by either taking over these new projects or retaining more of their ongoing projects, compared to unconstrained firms with no financially constrained competitors.

The model also contemplates the crowding-out channel. Note that in Ottonello and Winberry (2020) where adjustment costs are convex, when constrained firms already lack access to credit, they are largely insensitive to expected returns; whereas unconstrained firms are highly sensitive to expected returns. Thus, the cost of crowding out (or deterrence) by overinvesting is particularly high for unconstrained firms, but the effect on constrained firms is particularly low. This largely precludes crowding out. Nonconvex adjustment costs, however, allow unconstrained firms to take advantage of the inaction regime implied by the costs, in which firms choose not to invest at all to avoid adjustment costs. If unconstrained firms overinvest and depress future returns so much that some financially constrained competitors are pushed into the inaction regime, then these competitors will stop investing completely. This will dramatically increase the market share of unconstrained firms in the future, leading to higher payoffs that can potentially offset the cost of initial overinvestment. Yet how to derive empirically testable hypotheses from the theoretical intuition to disentangle the different channels remains a question. A corollary of the model is that the more financially constrained a firm is, the closer it is to the inaction regime, and the more likely it will be crowded out; therefore, if crowding out occurs, its effect must strictly increase in the tightness of financial constraints. Conversely, if no significant crowding out occurs, no differential impact should be apparent on firms with very tight and moderately tight financial constraints.

Using data for listed U.S. firms, I find that firm interactions have significant impact on investment, particularly during downturns. For financially unconstrained firms operating in financially constrained industries (i.e., with many financially constrained competitors), an average industry downturn is followed by increased capital expenditure amounting to 0.5-1% of total assets in one year and 1-1.5% in two years, compared to unconstrained firms in normal industries. Firm interactions are quantitatively large: the magnitude of such an increase is equivalent to the effect of a positive idiosyncratic shock of two standard deviations. In other words, having financially constrained competitors effectively allows financially unconstrained firms to better smooth investment during industry downturns.

In terms of causality, no sign of crowding out is apparent during industry downturns. Compared to moderately constrained firms, highly constrained firms are not differentially affected by interactions with their unconstrained competitors. As a result, firm interactions also generate countercyclical equilibrium effects on investment during industry downturns.

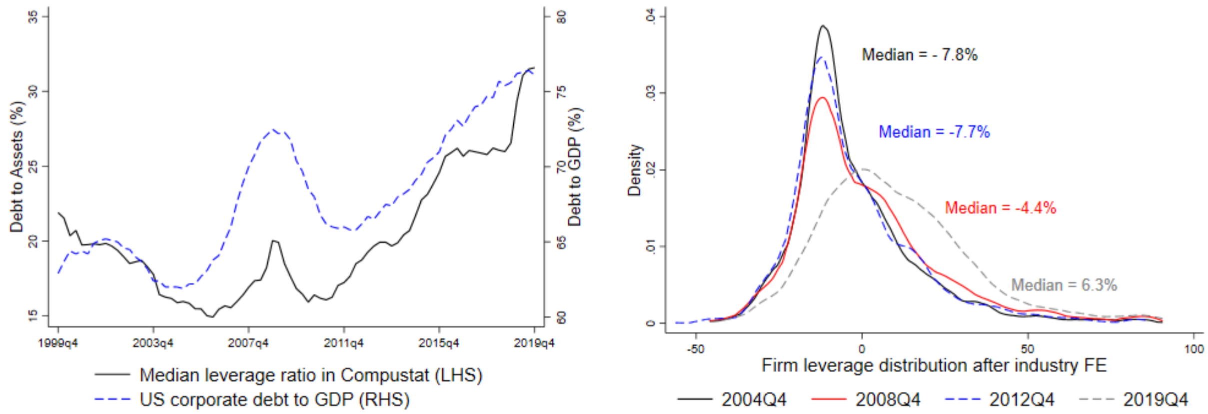
For idiosyncratic shocks firm interactions imply stronger competition effects. If a firm is surrounded by financially constrained (unconstrained) competitors, its investment reduction after a negative idiosyncratic shock will be 50% smaller (60% larger). This is likely because competitors intensify (soften) competition when they have more (less) financial resources, leaving the firm less (more) room to adjust.

To validate the economic reasoning, I examine additional aspects of firm interactions during industry downturns. First, the increase in investment by financially unconstrained firms is associated with substantial sales gains within the next four years except for firms with extraordinarily high market share. The sales gains justify firms' willingness to increase investment during downturns. Second, the magnitude of increased investment is positively correlated with product similarity, which is consistent with the notion that investment substitutability is stronger when firms are closer in the product space. Last but not least, the increase is almost entirely driven by small and medium firms, and it is larger in less concentrated industries. This correlation points to the potential role of concentration in firm interactions, but a causal explanation is beyond the scope of this paper.

The findings are robust to several changes in the estimations. First, the results do not change when using financial constraints and leverage separately. Second, results change little after controlling for triple interactions with revenue productivity, past lumpy investment, extraordinary market share, and Tobin's *q*. This mitigates potential omitted variable biases.

Finally, the results indicate that the interaction channel should play an important role in the macro implications of financial heterogeneity. Financial heterogeneity is enormous across firms. Evident in Figure 1, the cross-sectional dispersion of firm leverage is notable and easily dwarfs the movement of aggregate leverage. Similarly, firms' financial constraints, measured by the text-based index developed by Hoberg and Maksimovic (2015), are highly dispersed even when the cross-sectional mean moves little in the sample period (see Figure A.1). Because the intensity of firm interactions likely increases in the degree of financial heterogeneity, competitive interaction effects can be a substantial countercyclical force during downturns.

Related literature. This paper contributes to the literature in three ways. First and foremost, it offers a new channel to reconcile the discrepancy between micro and macro estimates in recent empirical studies on the impact of corporate debt. Firm-level studies often show negative effects of financial constraints during recessions, implying amplified aggregate output loss and impeded recoveries (e.g., Kalemli-Özcan, Laeven, and Moreno, 2022, Giroud and Mueller, 2016). According to Banerjee and Hofmann (2020), when firms become overindebted, they not only underperform in the short run but also remain weak after they recover, indicating long-term damage to these firms. By contrast, studies using aggregate time series sometimes contrast with their micro counterparts. Giesecke et al. (2011) find that, unlike banking crises, massive corporate bond defaults in the United States had little real effect in the past 150 years. Using historical data for 18 countries, Jordà et al. (2022) argue that corporate debt alone has no significant roleon aggregate output fluctuations. Likewise, using a panel of 30 countries, Mian, Sufi, and Verner (2017) find weak impact of corporate debt on GDP once controlling for household



(a) Aggregate leverage (b) Cross-sectional distribution

Notes: Panel (a) shows the aggregate leverage in the nonfinancial corporate sector from 1999Q4 to 2019Q4. The debt-to-GDP ratio is published by the BIS. Panel (b) plots the leverage distribution in the Compustat sample in 2005Q4 (trough) and 2019Q4 (peak) after removing the FIC 500 industry fixed effects as defined in Hoberg and Phillips (2016).

Figure 1: Dispersion of Corporate Leverage

debt. The countercyclical effect of firm interactions, which I document in this paper, could be a good candidate to explain the discrepancy between micro and macro focused studies.

Second, this paper contributes to the finance and industrial organization literature by examining the macro implications of firm interactions. A large swath of studies have shown that investment is affected by both competitive and strategic interactions of product market competitors (Dixit, 1980, Fudenberg and Tirole, 1984, Akdoğu and MacKay, 2008) and that competitors respond significantly to one another's financial constraints (Chevalier, 1995, MacKay and Phillips, 2005, Khanna and Tice, 2005, Leary and Roberts, 2014). In particular, Rauh (2006) and Grieser and Liu (2019) also find that financially unconstrained firms tend to increase investment when competitors are financially constrained. What is missing, in this literature, however, is an assessment of the equilibrium implication, precisely because it is difficult two disentangle between competitive and crowding out channels of interaction across firms. This paper provides a stylized theoretical argument and a feasible empirical strategy to disentangle these channels.[1]

Third, the empirical significance of firm interactions points to a new channel in the theory of financial heterogeneity. Recent researchers have studied heterogeneous responses to shocks (e.g., Ottonello and Winberry, 2020, Caglio, Darst, and Kalemli-Özcan, 2021), yet the rich interactions among financially heterogeneous firms and their aggregate implications are still less understood. By contrast, studies have shown important equilibrium implications of firm interactions under alternative market structures in many other fields, such as international (Amiti, Itskhoki, and Konings, 2019), banking (Corbae and D'Erasmo, 2021), and macro (Covarrubias, Gutiérrez, and Philippon, 2019, Baqaee, Farhi, and Sangani, 2021, de Loecker, Eeckhout, and

[1] Another strand of literature aims to recover equilibrium effects from DiD regressions using an indirect statistical approach. For example, Jiménez et al. (2020) and Mian, Sarto, and Sufi (2022) use the difference between the FE estimator and the OLS estimator to understand equilibrium effects.

Mongey, 2021, Wang and Werning, 2022). A natural next step would be to bring the empirical insights of this paper to models of financial heterogeneity.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 explains the empirical strategy to examine the interaction between shocks, firms' own financial constraints and those of its competitors. Section 4 presents the main firm-level results. Section 5 outlines the theoretical intuition and tests equilibrium implications to disentangle between the crowding out and competitive interaction channels. Section 6 concludes.

2 Data

The sample comprises listed nonfinancial firms in the United States from 1998 to 2016. The sample period covers three major cycles: two significant recessions in 2001 and 2008 as well as the smaller "earnings recession" in late 2015. Data after 2016 are not included because of the limited availability of financial constraint data from Hoberg and Maksimovic (2015), but indirectly they still enter the local projections through the dependent variable.[2] Below I explain how I construct important variables used in the analysis.

Product markets. Firms' competitors are identified using the text-based classifications by Hoberg and Phillips (2016). The two often-used classification systems, namely the North American Industry Classification System (NAICS) and the Standard Industrial Classification (SIC) system, are not ideal to analyze product markets because they are based on production processes instead of final products. By contrast, Hoberg and Phillips (2016) use 10-K product descriptions to develop text-based industry classifications with a continuous measure of similarity among firms, which are now widely used in the finance literature.

Two sets of classifications are available in Hoberg and Phillips (2016). One is the 10-K Text-Based Network Industry Classifications (TNIC) system, which applies a network structure and assigns a similarity score to each pair of firms in each year. The network structure also means that the TNIC, unlike the NAICS or the SIC, is not transitive. Even if A and B are close competitors and so are B and C, A and C are not necessarily close competitors. The other is the 10-K Text-Based Fixed Industry Classifications (FIC) system, which imposes the transitivity restriction on TNIC and produces a classification system that is analogous to the NAICS and the SIC. The most granular version available is the FIC-500, which includes 500 industries.

For the baseline analysis, I use the FIC-500 because its transitivity makes it more compatible with the fixed-effects regressions. In terms of granularity, FIC-500 is between the 4-digit NAICS and the 6-digit NAICS (see Figure A.2). Within the regression sample, the median (mean) number of firms in FIC-500 industries is 42 (57.1), whereas for 6-digit NAICS industries, the median (mean) is 36 (51.0).

Text-based financial constraints. I use the text-based measure by Hoberg and Maksimovic (2015) to access the tightness of a firm's financial constraints. The authors examine the liquidity and capital resources discussion in 10-K disclosures to determine whether firm management discuss delayed investment due to financial constraints. The textual analysis extends the small-

[2] That the sample does not cover the COVID recession is unfortunate, but the extraordinary and highly targeted financial policies implemented in 2020 would make controlling for policy treatments extremely difficult.

sample narrative approach used in Kaplan and Zingales (1997) and Hadlock and Pierce (2010) almost to the universe of Compustat firms. The latest version contains annual data from 1997 to 2015. Figure A.1 plots the distribution of this measure over time. Because I lag the data by one year, the sample period is from 1998 to 2016. Alternative measures of financial constraints are discussed in Sections 3.

Other firm-level characteristics. All other variables come from Compustat . Table 1 lists the variables and their definitions. Variables are quarterly except text-based financial constraints and labor productivity, which are annual. The latter two variables are thus lagged by 4 quarters instead of one when needed. For dummy variables, I use the 25th/75th percentile. Numerical variables are winsorized between the 2.5th and 97.5th percentiles unless otherwise noted.

Filters applied in the estimations. I exclude firms with nonpositive assets or sales. I also exclude firms in the following NAICS sectors: agriculture, finance (including finance and insurance, real estate and rental and leasing, and management of companies and enterprises), and unclassified. A firm is considered in one of those sectors if (1) it falls under one of them, or (2) more than 75% of its competitors are in one of these sectors.

When estimating shocks, I require each industry–quarter pair to have more than 10 firms with sales data. Firms need to have at least 20 observations to be included in the final sample. To improve industry-level measures, I add an industry size filter, which requires that (1) each industry should have at least 10 firms *within the regression sample* and (2) the largest firm in the industry should not have market share over 45% (which is the 95th percentile).

There are 4,856 unique firms in 127 product markets in the sample after applying all the filters. The average (median) asset value is 3,901 (374) million in real US$2009. The average (median) quarterly sales are 770 (86) million in real US$2009.

3 Empirical Model Specification

The focus of the analysis in this paper is the triple interaction in Equation 3.1.

$$\text{Shocks} \times \text{Firm's own financial constraints} \times \text{Peers' financial constraints} \tag{3.1}$$

Section 3.1 explains the construction of the shocks. Section 3.2 lays out the full specification. Sections 3.3 and 3.4 describe different measures of financial constraints and the control variables included in the analysis, respectively.

3.1 Estimating shocks

The shock estimation involves two steps. First, I decompose revenue growth into a sectoral term and a residual term à la di Giovanni, Levchenko, and Mejean (2014). Second, I define industry upturns and downturns as large changes in the sectoral component and convert them into binary dummies.

Decomposition. Let $\gamma_{i,t}$ be the year-over-year revenue growth of firm i operating in industry

Variable	Dimension	Type	Definition
Text-based financial constraints			
Text-based index	i,t	Numeric	The "Delay Investment Score" from Hoberg and Maksimovic (2015)
Unconstrained firm	i,t	Dummy	Text-bsaed index < -0.062 (25th percentile)
Constrained firm	i,t	Dummy	Text-bsaed index $\geq +0.036$ (75th percentile)
Unconstrained industry	i,t	Dummy	Over 47% (75th percentile) of firms are above the medium score
Constrained industry	i,t	Dummy	Below 27% (25th percentile) of firms are above the medium score
Leverage			
Firm leverage	i,t	Numeric	$\frac{\text{Debt}_{i,t}}{\text{Assets}_{i,t}} \times 100$ if $\text{Assets}_{i,t} > 0$, winsorized between $[0, 100]$
Peer leverage	i,t	Numeric	Average leverage of competitors
Low leverage	i,t	Dummy	Firm leverage $<$ Peer leverage -13.7 (25th percentile)
High leverage	i,t	Dummy	Firm leverage $\geq$ Peer leverage $+9.9$ (75th percentile)
Interest coverage ratio (ICR)			
ICR	i,t	Numeric	$\frac{\text{EBIT}_{i,t}}{\text{Interest expense}_{i,t}}$ if interest $\text{expense}_{i,t} > 0$, $\text{ICR}_{i,t} = +\infty$ if interest $\text{expense}_{i,t} \leq 0$
Low ICR	i,t	Dummy	ICR < 1
High ICR industry	i,t	Dummy	Over 80% (75th percentile) of firms have ICR ≥ 1
Low ICR industry	i,t	Dummy	Below 56% (25th percentile) of firms have ICR ≥ 1
Other variables			
Capital expenditure	i,t	Numeric	$\frac{\text{CAPX}_{i,t}}{\text{Assets}_{i,t-1}} \times 100$ for firms with $\text{Assets}_{i,t-1} > 0$
Productivity	i,t	Numeric	$\ln \frac{\text{Sales}_{i,t}}{\text{Employees}_{i,t}}$ for firms with $\text{Employees}_{i,t} > 0$
High productivity	i,t	Dummy	Productivity $\geq$ Peer average $+0.4$ (75th percentile)
Market share	i,t	Numeric	Nominal sales share in the industry
Tobin's q	i,t	Numeric	$\frac{\text{Assets}_{i,t} + \text{Market Equity}_{i,t} - \text{Book Equity}_{i,t}}{\text{Assets}_{i,t}}$

Notes: In Compustat, $\text{EBIT}_{i,t}$ is calculated as Interest $\text{expense}_{i,t}$ + Pre-tax $\text{income}_{i,t}$. For text-based index, if a firm has at least one non-missing value in the database, then its missing observations (if any) are treated as neither constrained nor unconstrained when I compute the dummies.

Table 1: Definitions of Key Variables

n.[3] Because no multi-industry firm is included, I do not add n to the subscript for simplicity.

$$\gamma_{i,t} = \ln\left(\frac{\text{Sales}_{i,t}}{\text{Sales}_{i,t-4}}\right) \times 100 \tag{3.2}$$

Following di Giovanni, Levchenko, and Mejean (2014), I use Equation 3.3 to decompose nominal sales growth.[4] The full derivation is in Appendix B. Here $\delta_{n,t}$ is the macro sectoral component specific to industry n where firm i operates, and $\epsilon_{i,t}$ is the firm-specific idiosyncratic

[3] I do not use quarter-over-quarter growth because seasonal adjustment may be too demanding at the firm level.

[4] One would be correct to point out that including firm i in Equation 3.3 may bias the estimated $\delta_{n,t}$. For instance, if firm i has extraordinary sales growth at t, then the estimated $\delta_{n,t}$, which is effectively the industry average of sales growth, will be affected by firm i. One way is to omit firm i when estimating the sectoral component for firm i, but then fixed effects will not fully absorb industry-level variables, leaving the results more complicated. I mitigate this problem by (i) winsorizing sales growth at the 2.5th and 97.5th percentiles and (ii) requiring at least 10 firms. On average, 57 firms are in each industry in the regression sample, which likely eliminates this problem.

component.

$$\gamma_{i,t} = \delta_{n,t} + \epsilon_{i,t} \tag{3.3}$$

Table A.2 shows the properties of the estimated shocks. Columns (5) and (6) indicate that the persistence of estimated components looks reasonable. Equation 3.3 is notably prone to a size-dependent bias due to the high correlation between size and demand elasticity, which is particularly relevant because large firms are omnipresent in Compustat. This size-dependent bias is empirically evident in columns (2) and (4) of Table A.2, where the size factor is included (see Appendix B for theoretical analysis). This will be addressed in the next step.

Filtering shocks. After the decomposition I filter the sectoral component $\delta_{n,t}$ and consider only large values in absolute terms. This ensures that my results are not driven by fluctuations around the mean, which can hardly be considered upturns or downturns. Note also a profound time trend in $\delta_{n,t}$ (see Figure 2). Without imposing more assumptions, I use a simple OLS to remove the linear time trend. Then, I define industry downturns as having the detrended $\delta_{n,t}$ below the 25th percentile and industry upturns as having the detrended $\delta_{n,t}$ above the 75th percentile. Figure 2 shows the distribution of $\delta_{n,t}$ as well as the bands.

Next, I convert industry upturns and downturns into binary dummies so that I do not impose linearity on them. The interpretation of the dummies, therefore, is an average upturn or downturn. By converting $\delta_{n,t}$ into dummies, I also mitigate the size-dependent bias from the first step because it is unlikely to be large enough to systematically alter the dummies. I denote the upturn dummy as $\delta^{+}_{n,t}$ and the downturn dummy as $\delta^{-}_{n,t}$.

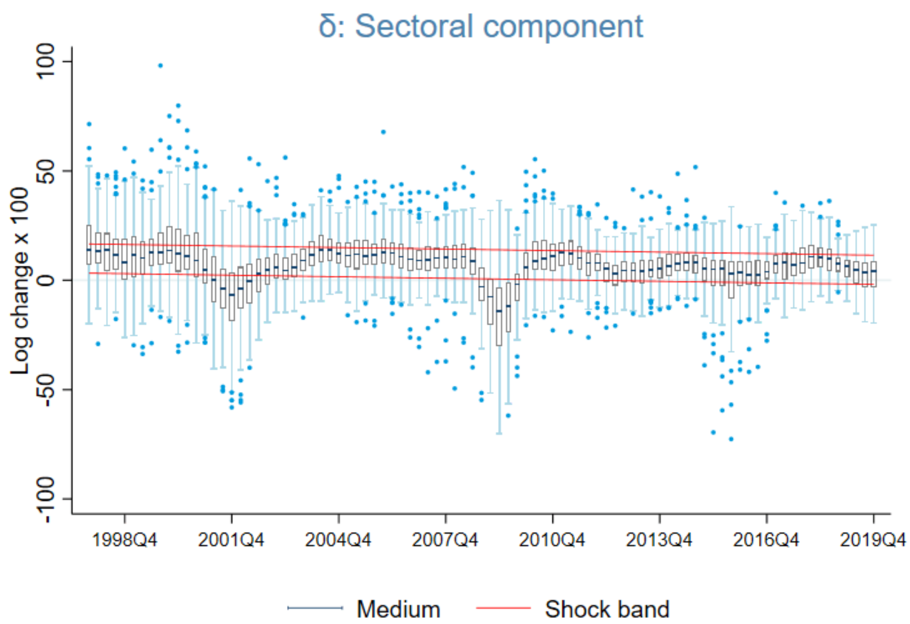
$$\delta^{-}_{n,t} = \mathbb{1}_{\delta^{\text{detrended}}_{n,t} < 25\text{th}}, \quad \delta^{+}_{n,t} = \mathbb{1}_{\delta^{\text{detrended}}_{n,t} > 75\text{th}} \tag{3.4}$$

Third, I normalize the idiosyncratic residual $\epsilon_{i,t}$ so that the interpretation is an idiosyncratic shock of one standard deviation.

3.2 Specification

Pooling together the three shock components, we have Equation 3.5 as the basic specification to examine firm interactions. All regressors have three additional lags, which I do not spell out for simplicity.

$$\begin{aligned}
y_{i,t+h} = {} & \underbrace{\beta_1 \cdot \delta^{-}_{n,t} \cdot \mathrm{FC}_{i,t-1} \cdot \mathrm{FC}^{peer}_{n,t-1} + \beta_2 \cdot \delta^{-}_{n,t} \cdot \mathrm{FC}_{i,t-1}}_{\text{Downturns}} \\
& + \underbrace{\beta'_1 \cdot \delta^{+}_{n,t} \cdot \mathrm{FC}_{i,t-1} \cdot \mathrm{FC}^{peer}_{n,t-1} + \beta'_2 \cdot \delta^{+}_{n,t} \cdot \mathrm{FC}_{i,t-1}}_{\text{Upturns}} \\
& + \underbrace{\tilde{\beta}_1 \cdot \epsilon_{i,t} \cdot \mathrm{FC}_{i,t-1} \cdot \mathrm{FC}^{peer}_{n,t-1} + \tilde{\beta}_2 \cdot \epsilon_{i,t} \cdot \mathrm{FC}_{i,t-1} + \tilde{\beta}_3 \cdot \epsilon_{i,t} \cdot \mathrm{FC}^{peer}_{n,t-1} + \tilde{\beta}_4 \cdot \epsilon_{i,t}}_{\text{Idiosyncratic}} \qquad (3.5) \\
& + \beta_5 \cdot \mathrm{FC}_{i,t-1} \cdot \mathrm{FC}^{peer}_{n,t-1} + \beta_6 \cdot \mathrm{FC}_{i,t-1} \\
& + \text{Full interaction controls}_{i,t} + \text{Other controls}_{i,t-1} + \text{Lags} \\
& + \text{Firm FE}_i + \text{Time FE}_t + \text{FIC Industry x Time FE}_{n,t} + \zeta_{i,t}
\end{aligned}$$



Notes: The figure shows the distribution of the sectoral component, $\delta_{n,t}$, at the industry level. The box plot consists of the median value, 25th and 75th percentiles, adjacent values, and outliers. The bands are calculated using the 25th and 75th percentiles after removing a linear time trend from $\delta_{n,t}$.

Figure 2: Distribution of the Sectoral Component

Since I examine the investment channel, I set the dependent variable, $y_{i,t+h}$, as firm i's future capital expenditure (CAPX), either cumulative or quarterly. Because investment plans can be predetermined at the quarterly frequency, I calculate cumulative CAPX as the expenditure from $t+1$ to $t+h$ normalized by lagged total assets:

$$y^{\text{cum}}_{i,t+h} = \frac{\sum_{k=1}^{h} \text{CAPX}_{i,t+k}}{\text{Assets}_{i,t-1}}, \quad y_{i,t+h} = \frac{\text{CAPX}_{i,t+h}}{\text{Assets}_{i,t-1}}$$

On the right-hand side, shock terms ($\delta^{-}_{i,t}$, $\delta^{+}_{i,t}$, $\epsilon_{i,t}$) are defined above. $\text{FC}_{i,t-1}$ and $\text{FC}^{peer}_{n,t-1}$ summarize the lagged financial constraints of firm i and its competitors, respectively. Different measures are discussed in Section 3.3. Full interaction controls and other controls are described in Section 3.4. Standard errors are clustered by industry, firm, and time.

3.3 Measures of financial constraints

Both $\text{FC}_{i,t-1}$ and $\text{FC}^{peer}_{n,t-1}$ are binary dummies unless otherwise noted. The main measure is the text-based financial constraint measure by Hoberg and Maksimovic (2015), given its high consistency across industries and time. I add additional measures for robustness. Plain-vanilla leverage is the first candidate to consider given its wide use in both micro studies (e.g., Khanna and Tice, 2005, Kalemli-Özcan, Laeven, and Moreno, 2022) and macro studies (e.g., Jordà et al., 2022), even though strictly speaking it measures solvency rather than financial constraints. The

Size-Age (SA) index by Hadlock and Pierce (2010) and the Whited-Wu (WW) index by Whited and Wu (2006) are also widely used in the finance literature. Finally, the interest coverage ratio (ICR) is also a traditional measure, though it measures liquidity rather than financial constraints.

Given the many fixed effects included in Equation 3.5, examining whether these measures have sufficient statistical power after fixed effects are included is necessary. For binary dummies based on the WW and SA indices, 74–82% and 77–86% of the variation turns out to be absorbed by industry–time and firm fixed effects, depending on the threshold. For binary dummies based on the text-based measure, leverage, and the ICR, fixed effects account for only 47–48%, 55–59%, and 47–50%, respectively. Consequently, the WW index and SA index are considered far less informative than the other three measures.

Dummies based on the text-based measure, leverage, and the ICR are defined in Table 1. I use the text-based measure at both the firm level and the industry level. For financially unconstrained firms, I use the text-based measure and leverage in parallel and then compare the two sets of results. For financially unconstrained industries, I use the text-based measure and the ICR in parallel.

3.4 Control variables

My set of control variables is broadly in line with the control variables used in the literature (e.g., Rauh, 2006, Hoberg and Maksimovic, 2015, Grieser and Liu, 2019).[5] For important control variables, I include the full interactions with shock terms and peers' financial constraints.

Productivity. To mitigate the concern that insufficient controls for firm productivity, or firm quality in general, may bias the results, I add full interactions with a firm's labor productivity measure (relative to the peer average) as additional controls. To absorb any potential nonlinear effect of productivity, I use a categorical variable, which partitions productivity into 5 categories from very low to very high: 5th, 10th, 90th, and 95th percentiles. The reference group is the middle one from the 10th to 90th percentiles (i.e., firms with normal productivity).

Productivity is only available at the annual frequency, so it must be lagged by one year instead of one quarter; therefore, full productivity controls include the following triple interaction and all associated terms and lags.

$$\text{Productivity interactions}_{i,t} = \text{Shocks}_{i,t} \times \text{Productivity ladder}_{i,t-4} \times \text{FC}^{peer}_{n,t-1} + \cdots$$

Lumpy investments. If investment is lumpy, large investment in the past may result in lower investment in the near future. The "lumpy investment" variable is a categorical variable using lagged capital expenditure that divides lagged CAPX at the 90th and 95th percentiles, and the reference group is the one below the 90th percentile (i.e., firms with no past lumpy investment). Similar to productivity controls, I use a triple interaction and all associated terms to control for lumpy investments.

[5] Note that I do not control for cash flows because cash flows are highly correlated with the sales-based shock terms. I also do not control for leverage as I already use it for $\text{FC}_{i,t-1}$.

Extraordinary market share. Firms with extraordinary size relative to the industry may also behave differently (e.g., Crouzet and Mehrotra, 2020), a situation I will explore later in Section 4. In the baseline specification, I include a triple interaction and all associated terms to control for extraordinary market share. The categorical variable for market share again uses the 90th and 95th percentiles as thresholds, and the reference group is the group of firms with non-extraordinary market share.

Tobin's *q*. Tobin's q, defined in Table 1, is widely used to control for a firm's investment opportunities perceived by the market (e.g., Lang, Ofek, and Stulz, 1996). Similar to previous control variables, I use a categorical variable to partition Tobin's q at the 5th, 10th, 90th, and 95th percentiles. The reference group being the middle category (i.e., firms with normal Tobin's q). Then I add the full interactions with the categorical variable to control for Tobin's q.

Other controls. For non-interacted control variables, I only include lagged CAPX, peers' average CAPX, and leverage given that the interacted controls are already tight.

4 Empirical Results on Firm Interactions

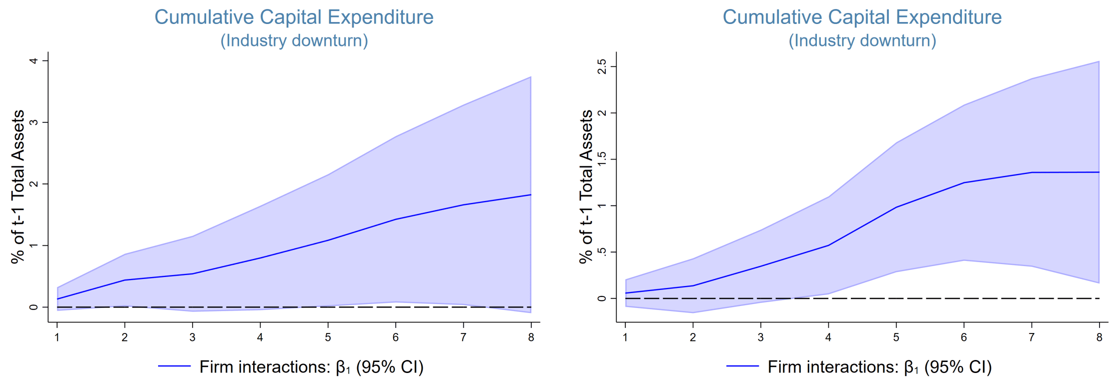
In this section I present the empirical results of estimating Equation 3.5 without taking a stance on the causal interpretation. Table A.1 lists the summary statistics of key variables within the regression sample. Equilibrium implications are analyzed and tested in Section 5.

4.1 Firm interactions over the cycle

Industry downturns. As previously discussed, we expect financially unconstrained firms in financially constrained industries to relatively increase their investment during downturns, regardless of whether they attempt to crowd out competitors or not. This is confirmed across specifications and measures.

Table 2 reports the baseline results using (i) the 6-quarter ahead cumulative CAPX, $y^{\text{cum}}_{i,t+6}$, as the dependent variable and (ii) the interaction between financially unconstrained firms and financially constrained industries to capture firm interactions. Financially constrained industries are measured by the text-based "unconstrained industry" dummy as defined in Table 1, whereas financially unconstrained firms are measured by the "low leverage" dummy in columns (1) to (4) and by the text-based "unconstrained firm" dummy in columns (5) to (8). Under both measures β_1 is 1.1-1.5 after 6 quarters, and it remains significant after I add all fixed effects, the industry size filter, and full interaction controls. That results are highly consistent across two different measures of financial constraints further strengthens the robustness of the results.

It is worth noting that the GFC period also coincides with a banking crisis. Previous studies (e.g., Kalemli-Özcan, Laeven, and Moreno, 2022, Giesecke et al., 2011, Jordà et al., 2022) all control for banking crises because the credit supply channel is very different from the corporate balance sheet channel. To test whether the firm interaction channel remains effective during the GFC period, I include the GFC period only in the last estimations (columns (4) and (8)). Including the GFC period only marginally moderate results from columns (3) and (7) to columns (4) and (8).



(a) $\text{FC}_{i,t-1}$: Leverage　　(b) $\text{FC}_{i,t-1}$: Text-based

Notes: The two local projections correspond to β_1 in columns (4) and (8) in Table 2. β_1 is the cumulative increase in investment by financially unconstrained firms in financially constrained industries (text-based) during industry downturns. In Panel (a) unconstrained firms are those with low leverage relative to competitors. In Panel (b) unconstrained firms are measured by text-based constraints.

Figure 3: Firm Interactions during Industry Downturns

To show the dynamic effects of firm interactions, I plot local projections of β_1 in Figure 3, which correspond to columns (4) and (8) in Table 2. Under both measures β_1 stabilizes at 1-1.5% of pre-shock assets after 8 quarters with results using the text-based measure being more significant. For comparison, this is approximately two times as large as the effect of an one-standard-deviation idiosyncratic shock ($\tilde{\beta}_4$), signifying the quantitative importance of β_1.

Industry upturns. As expected, firm interactions are not sizable during upturns because financially constrained firms do not need to forgo investment opportunities during these periods.

Idiosyncratic shocks. Idiosyncratic shocks also confirm the importance of competitors' financial constraints. $\tilde{\beta}_3$, which captures how a firm's response to its idiosyncratic shocks is affected by competitors, is both large and significant. The insignificance of other interactions means that the competitor effect captured by $\tilde{\beta}_3$ is largely invariant in the firm's own financial constraints.

To understand the exact interpretation of $\tilde{\beta}_3$, I further break down the idiosyncratic shocks into positive ones and negative ones. Results using different measures are reported in Tables A.3, A.4, and A.5. Regardless of a firm's own financial constraints, if it is surrounded by financially constrained competitors, its investment elasticity to negative idiosyncratic shocks will be about 50% smaller in all specifications with high significance (Tables A.3). By contrast, if it is surrounded by highly liquid competitors measured by the ICR, its investment elasticity to negative idiosyncratic shocks will be amplified by about 60%, but the significance is slightly weaker (Table A.5).[6]

The correlation between a firm's response to negative idiosyncratic shocks and its competitors' financial constraints is consistent with the competition channel in the finance-IO litera-

[6]Interestingly, if I use the text-based measure to identify financially unconstrained competitors, results will be even less significant (Table A.4). A grain of salt is, therefore, needed here.

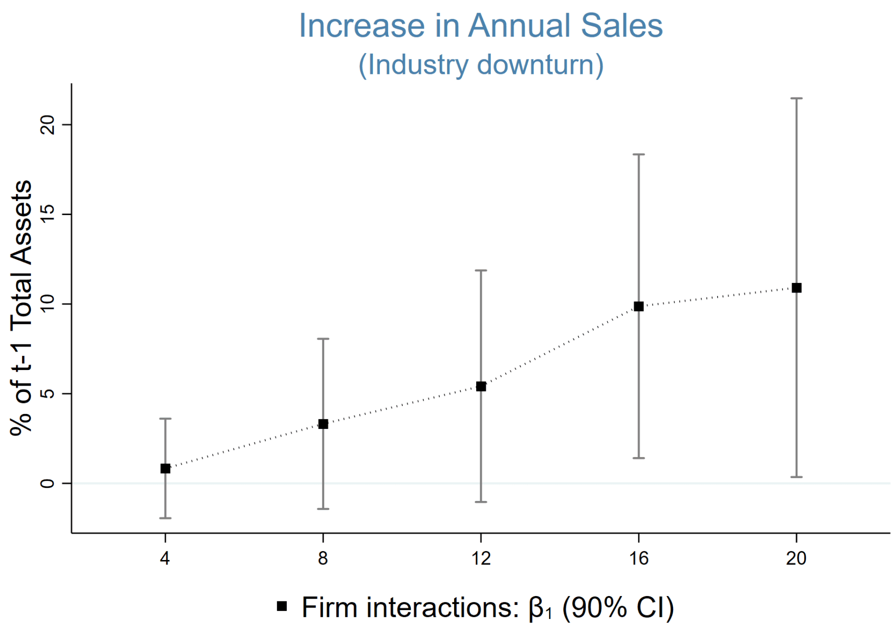
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Financially unconstrained firms							
	Leverage dummy				Text-based dummy			
Industry downturns								
Downturn x Dummy	-0.07	-0.16	-0.19	-0.12	0.13	0.09	0.03	-0.00
	(0.25)	(0.28)	(0.30)	(0.25)	(0.16)	(0.19)	(0.21)	(0.17)
Downturn x Dummy	1.21**	1.72**	1.51**	1.43**	0.53	1.06***	1.25***	1.16***
x Constrained peers (β_1)	(0.47)	(0.67)	(0.68)	(0.69)	(0.37)	(0.38)	(0.43)	(0.38)
Industry upturns								
Upturn x Dummy	0.10	-0.15	-0.18	-0.17	-0.27**	-0.16	-0.03	-0.04
	(0.28)	(0.32)	(0.34)	(0.32)	(0.12)	(0.14)	(0.17)	(0.15)
Upturn x Dummy	-0.07	0.25	0.42	0.37	0.09	0.26	0.39	0.25
x Constrained peers	(0.42)	(0.45)	(0.48)	(0.43)	(0.44)	(0.44)	(0.46)	(0.37)
Idiosyncratic shocks								
Idiosyncratic shocks ($\tilde{\beta}_4$)	0.73***	0.74***	0.62***	0.63***	0.74***	0.75***	0.60***	0.65***
	(0.09)	(0.10)	(0.08)	(0.07)	(0.09)	(0.09)	(0.08)	(0.07)
Idio. shocks x Dummy	0.02	0.06	0.07	0.09	-0.03	0.01	0.09	-0.02
	(0.13)	(0.15)	(0.16)	(0.14)	(0.08)	(0.08)	(0.10)	(0.10)
Idio. shocks x	-0.36***	-0.41***	-0.23**	-0.23**	-0.33***	-0.36***	-0.18	-0.23**
Constrained peers ($\tilde{\beta}_3$)	(0.09)	(0.11)	(0.09)	(0.09)	(0.12)	(0.13)	(0.11)	(0.11)
Idio. shocks x Dummy	0.12	0.06	-0.00	-0.08	-0.10	-0.25	-0.33*	-0.19
x Constrained peers	(0.26)	(0.29)	(0.27)	(0.23)	(0.16)	(0.16)	(0.19)	(0.18)
Other interactions								
Dummy	0.88***	1.02***	0.88***	0.94***	0.12	0.08	0.07	-0.03
	(0.22)	(0.24)	(0.25)	(0.24)	(0.14)	(0.14)	(0.15)	(0.13)
Constrained peers	-0.01	-0.33	-0.24	-0.23	-0.64**	-0.69**	-0.74**	-0.58*
x Dummy	(0.44)	(0.42)	(0.46)	(0.46)	(0.28)	(0.33)	(0.36)	(0.32)
FIC, Firm, Time FE	Y	Y	Y	Y	Y	Y	Y	Y
FIC x Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry size		Y	Y	Y		Y	Y	Y
Full interaction controls			Y	Y			Y	Y
GFC period				Y				Y
R^2	0.737	0.707	0.722	0.713	0.736	0.705	0.721	0.712
Within R^2	0.086	0.079	0.121	0.124	0.085	0.078	0.121	0.124
N	125,241	98,602	95,112	112,990	122,133	96,173	92,869	110,455
Firms	4,625	4,312	4,208	4,272	4,440	4,147	4,052	4,111
FIC industries	124	95	95	96	123	95	95	96

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Competitors' financial constraints (i.e. industry-level) are measured by the text-based measure. The dependent variable is $y^{\text{cum}}_{i,t+4}$. In the first four columns, firm-level financial constraints are measured by leverage, whereas in the last four columns, I use the text-based measure. The key coefficient, β_1, is consistent across measures and specifications. Standard errors are clustered by industry, firm, and quarter.

Table 2: Baseline Results ($h = 6$)

ture (e.g., Chevalier, 1995, Khanna and Tice, 2005). If a firm faces a negative idiosyncratic shock, its competitors can compete more aggressively when they have abundant financial resources, leaving it less room to adjust (and vice versa). This also implies strong effects of crowding out on firms facing negative idiosyncratic shocks in the presence of financially unconstrained competitors; however, this does not mean that crowding out is also significant during industry downturns because idiosyncratic shocks and industrywide shocks are different types of shocks. The exact interpretation during industry downturns will be examined in Section 5.



Notes: The figure shows the medium-term gains in sales by small and medium firms financially unconstrained firms in financially constrained industries after a downturn. The dependent variable is defined in Equation 4.1. The horizon ranges from 4 to 20 quarters. Financial constrains are measured by the text-based measure, and the specification corresponds to column (3) in Table A.3.

Figure 4: Medium-term Gains in Sales for Small and Medium Firms

4.2 Medium-term gains in sales

The significant increase in investment associated with β_1 should lead to higher sales and market share in the future. Given that most of the investment occurs 1-2 years after a downturn, the sales gains should occur only afterwards.

To test this hypothesis, I use the change in future sales, normalized by the pre-shock asset values, as the dependent variable.[7] In particular, to minimize the influence of seasonality, I use the rolling cumulative sales over four quarter (analogous to annual sales) defined in Equation 4.1. I winsorize the dependent variable at 5 and 95 percentiles.

$$y^{\Delta sales}_{i,t+h} = \frac{\text{Cum. Sales}_{i,t+h} - \text{Cum. Sales}_{i,t-1}}{\text{Assets}_{i,t-1}} \tag{4.1}$$

where Cum. $\text{Sales}_{i,t} = \sum_{k=0}^{3} \text{Sales}_{i,t-k}$.

Two additional issues should be noted. First, as I will show below, extraordinarily large firms have much smaller (if any) investment responses for several potential reasons. Regardless of the causal explanation, this would surely mute their sales gains. Therefore, I focus only on small and medium unconstrained firms (those with market share below the 75th percentile, or

[7] Sales changes may not be normalized by either firm-level or industry-level current sales because sales growth already enters the right hand side through $\delta_{n,t}$ and $\epsilon_{i,t}$.

2.5% of industrywide sales). Second, I restrict the sample to firms with non-missing sales in 16 quarters (i.e. $y^{\Delta sales}_{i,t+16} \neq \text{NA}$). This eliminates composition changes caused by firm exit, which can be significant given the very long horizon.

Figure 4 plots the local projections of β_1 for small and medium firms that are financially unconstrained, which measure the increase in sales associated with the increased investment discussed above. Sales starts to move up marginally in 2 years after a downturn, and the increase stabilizes at 10% of pre-shock assets after 4 years. The magnitude is also quantitatively large: a 10% increase is as large as the effect of an idiosyncratic shock of one standard deviation (see Table A.6 for more regression outputs). Despite the long horizon, the increase is significant at the 10% level in 16 quarters. In addition, the timing of the sales increase is highly consistent with most investment occurring in the second year after a downturn, implying a reasonable lag from capital expenditure to actual production and distribution.

4.3 Firm and industry heterogeneity beyond financing constraints

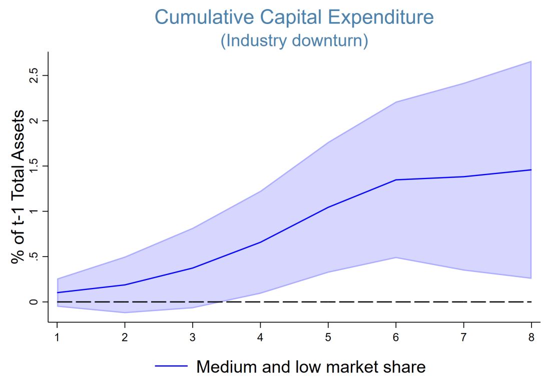
Next, I explore heterogeneity in some firm and industry characteristics.

Firm market share. To understand how market share is correlated with firm interactions, I split firms (i.e., $\text{FC}_{i,t-1}$) into two groups: extraordinarily large firms with market share above the 75th percentile (2.5% of industrywide sales) and small and medium firms with market share below the 75th percentile.[8] For small and medium firms (Panel (a) of Figure 5), β_1 is not only larger but also more significant, whereas for firms with extraordinarily high market share (Panel (b)), the effect disappears completely. This means that firm interactions captured by β_1 are almost entirely driven by small and medium firms. One mechanical explanation is that for extraordinarily large firms, competitors are too small to trigger measurable firm interactions, and even if they raise investment, the result could be minimal after division by assets. Alternatively, there may be unobserved industry characteristics shared by these large firms that mute firm interactions. By construction, it is more likely to find extraordinarily large firms in highly concentrated industries, so extraordinarily large firms likely share unobserved industry characteristics correlated with industry concentration. Third, large firms may have different strategic considerations that lead to inaction during downturns. Nonetheless, finding the exact causal explanation is beyond the scope of this paper.

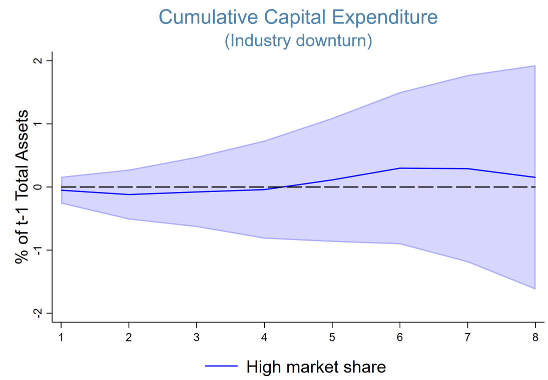
Product similarity. The second characteristic to test is product similarity, measured by the text-based similarity score from Hoberg and Phillips (2016). Intuitively, the closer firms are in the product space, the easier to compete and substitute. As a result, the magnitude of firm interactions should be larger when firms have more similar products. Panels (c) and (d) confirm the intuition. For firms with very low product similarity vis-à-vis their competitors (below the 25th percentile), β_1 is small and insignificant, but for other firms β_1 remains unchanged.

Industry concentration. Third, I test the role of industry concentration, measured by the TNIC Herfindahl-Hirschman Index (HHI) developed by Hoberg and Phillips (2016). β_1 is much smaller and insignificant in high-HHI industries (above the 75th percentile). This potentially implies much weaker countercyclical effects of firm interactions during downturns in highly

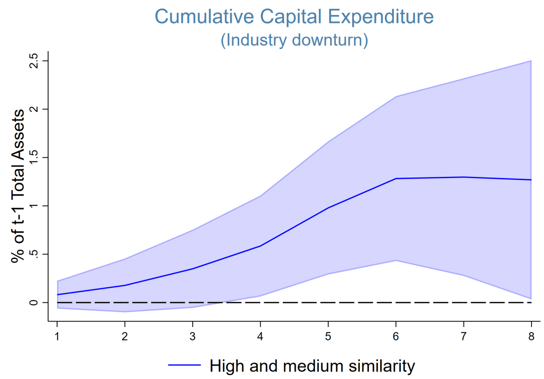
[8] Full interaction controls for market share (see Section 3) are not added here; otherwise, doing so would artificially lower the estimates for firms with high market share.



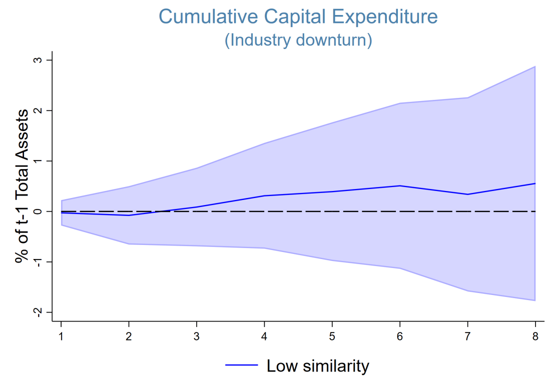
(a) Market share ≤ 75th



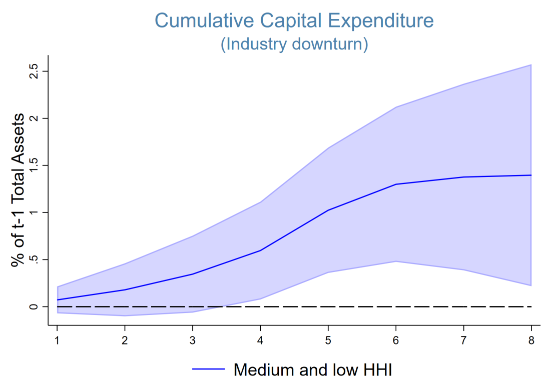
(b) Market share > 75th



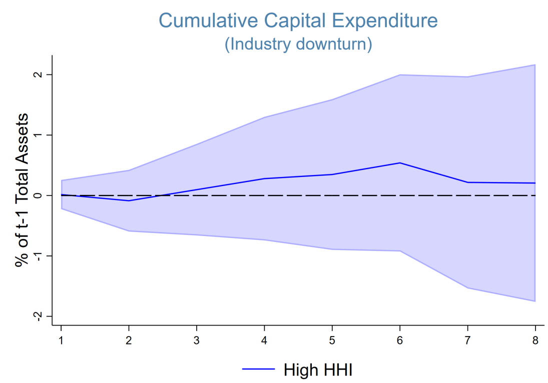
(c) Product similarity > 25th



(d) Product similarity ≤ 25th



(e) HHI ≤ 75th



(f) HHI > 75th

Notes: This figure extends Panel (b) in Figure 3 by splitting the sample by firm market share, firm product similarity, and industry HHI. Confidence intervals are 95% in all panels. Thresholds are indicated in panel titles. Full interaction controls for market share (see Section 3) are not added in Panels (a) and (b). Financial constrains are measured by the text-based measure, and the specification corresponds to column (4) in Table A.3.

Figure 5: Firm and Industry Characteristics and β_1

concentrated industries. Similar to market share, concentration is highly endogenous, and providing a causal explanation is beyond the scope of this paper.

5 Equilibrium implications of β_1

As discussed in the introduction, the interpretation of β_1 is not theory-free because it can be driven by either the "competitive interaction" or "crowding-out" channel. In this section, I offer a simple but empirically testable way distinguish between the two channels.

5.1 Theoretical intuition

Following the intuition in Ottonello and Winberry (2020), I conceptualize the investment problem using a marginal cost (MC) curve and a marginal benefit (MB) curve. In Ottonello and Winberry (2020), the borrowing constraint pins down the convexity of the MC curve because the marginal cost of capital is largely affected by the marginal cost of credit. The MC curve is highly convex for financially constrained firms but rather flat for unconstrained firms. The MB curve is downward sloping because capital has diminishing marginal returns.

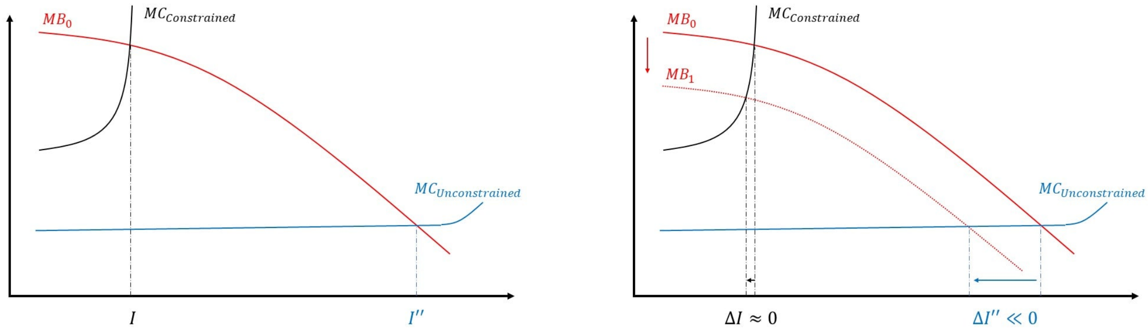
To analyze interactions among financially heterogeneous firms, I deviate from Ottonello and Winberry (2020) in two ways. First, I assume nonconvex adjustment costs, which are empirically important at the micro level (Doms and Dunne, 1998, Cooper and Haltiwanger, 2006).[9] More importantly, financially constrained firms are often those who invest less, and nonconvex costs disproportionally affect firms with low investment. This correlation further justifies the inclusion of nonconvex costs in this heterogeneous setting. Second, I assume that investment projects are substitutes for firms in the same product market. This assumption allows firm interactions to effect through the MB curve: a firm's increase in investment may lower the expected returns of its competitors' investment and thus discourage competitors from investing. Nonconvex costs and the substitutability of investment together make possible the deterrence effect of investment, in which a firm may strategically use investment as a commitment to expand output and reduce industrywide profitability to deter rivals from entering or expanding (Dixit, 1980, Smiley, 1988, Smiley, 2018). The deterrence effect is central in the analysis of the crowding out interpretation below. Finally, I will show that the conclusion also holds if firms can interact through the MC curve, i,e., if firms can directly affect competitors' financial constraints.

Basic mechanisms. Panel (a) in Figure 6 depicts the MB and MC curves for financially constrained and unconstrained firms. I allow MC curves to differ in both level and convexity for greater generality. The MB curve captures the industrywide marginal returns and is shared by all firms, as β_1 is the coefficient on the triple interaction with industry downturns. Adjustment costs are deducted from the MB curve. With nonconvex adjustment costs deducted from investment returns, the MB curve becomes concave on the left, that is, when investment is small.

Panel (b) in Figure 6 shows how firms respond when the MB curve shifts downward from MB_0 to MB_1 in the absence of firm interactions. Similar to Ottonello and Winberry (2020), financially constrained firms are far less sensitive to changes in the MB curve than unconstrained firms because of the convexity of the MC curve ($\Delta I \approx 0$ and $\Delta I'' \ll 0$ in the figure).

Firm interactions with no crowding out. Now I show how firm interactions cause firms to deviate from the solution in Figure 6, and the deviation is exactly what β_1 aims to capture.

[9] Ottonello and Winberry (2020) include only convex adjustment costs to reduce the sensitivity of aggregate investment to interest rates. This is not a concern here because I do not need to match aggregate moments.



(a) MC and MB curves

(b) Changes in expected returns

Notes: The figure depicts the basic model with no direct firm interactions. Panel (a) shows the static equilibrium for financially constrained and unconstrained firms. Panel (b) shows their responses to a downward shift of the marginal benefit (MB) curve, holding the marginal cost (MC) curve constant. In general, unconstrained firms are more sensitive to shifts of the MB curve than constrained firms are.

Figure 6: Basic Setting Without Firm Interactions

Let's first look at the case without strategic crowding out. When a negative shock hits and some firms face tightening financial constraints, they reduce investment dramatically; *ceteris paribus*, doing so raises the MB curve for all firms in the same industry.[10] Because unconstrained firms are most sensitive to shifts of the MB curve, again *ceteris paribus*, they respond by increasing their own investment. The larger the share of constrained firms, the larger the increase by unconstrained firms. More importantly, financially constrained firms, while severely affected by the shock, are unlikely *further* affected by firm interactions. This is because even if firm interactions may again move the MB curve, financially constrained firms are insensitive to changes in MB as we already know from Panel (b) in Figure 6.

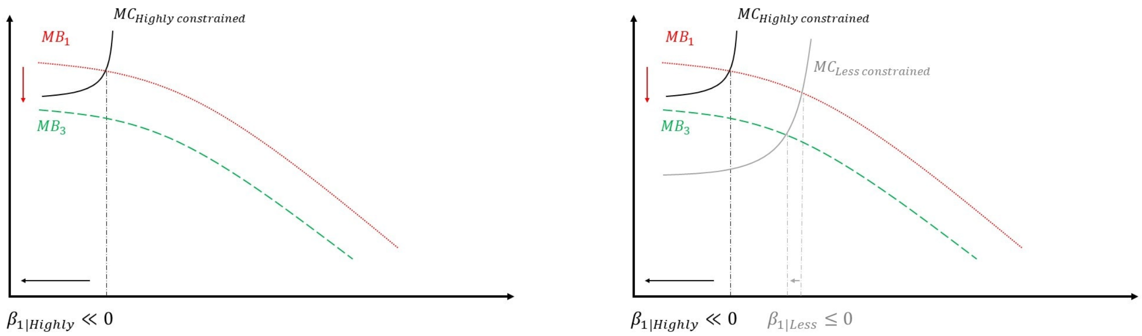
If we separate financially constrained firms into highly constrained and less constrained ones, the rationale above implies that neither of them should be negatively affected. Denote the effect of firm interactions during downturns on group i in a financially constrained industry as $\beta_{1\,|\,i}$. Then we have Hypothesis 5.1.

$$\beta_{1\,|\,\text{Highly constrained}} = \beta_{1\,|\,\text{Less constrained}} = 0 \ll \beta_{1\,|\,\text{Unconstrained}} \tag{5.1}$$

Strategic crowding out through the MB curve. Is strategic crowding out possible in this diagram? No, if there are no nonconvex adjustment costs. On the one hand, if an unconstrained firm wants to proactively increase investment to further drive down the MB curve, it will not have much effect on already constrained firms. On the other hand, the cost of overinvestment will be particularly high given its high sensitivity to returns.

Nonconvex adjustment costs provide an exception through the deterrence effect explained

[10]The shock shifts the MB curve downward and tightens the MC curve, probably considerably; but such changes are already absorbed by the shock term and all the double interactions. As for β_1 per se, all that matters is the response to each other's conditions, not to the common shock.



(a) Highly constrained firms　　(b) Less constrained firms

Notes: The figure shows the differential impact on financially constrained firms under strategic crowding out. Unconstrained firms are not included in the figure for simplicity.

Figure 7: Strategic Crowding Out

above. A well-known implication of nonconvex adjustment costs is that they give rise to the inaction regime – an area where firms choose not to invest at all to avoid the costs. A plausible solution for unconstrained firms is to increase investment dramatically, such that the MB curve is low enough to push highly constrained firms into the inaction regime. Highly constrained firms will stop investment completely and shrink gradually; therefore, unconstrained firms can gain more market share and higher markup in the long term, which may overweight the short-term cost of overinvestment.

Panel (a) in Figure 7 visualizes the crowding out effect on highly constrained firms.[11] Note that the distance to the inaction regime increases in the tightness of financial constraints, so the effect of crowding out is stronger for highly constrained firms but weaker for less constrained firms as shown in Panel (b). The differential impact on highly and less constrained firms provides a new hypothesis that directly contradicts Hypothesis 5.1:

$$\beta_{1\,|\,\text{Highly constrained}} \ll \beta_{1\,|\,\text{Less constrained}} \leq 0 \ll \beta_{1\,|\,\text{Unconstrained}} \tag{5.2}$$

Strategic crowding out through the MC curve. Hypothesis 5.1 still holds when strategic crowding out happens through the MC curve. If the financial constraint is earnings-based, a firm may lower its prices to reduce the earnings of its competitors and thus tighten their financial constraints. If the financial constraint is an asset-based collateral constraint, a firm may overinvest in capital to lower the price of capital, which also tightens competitors' financial constraints. In either case, highly constrained firms are always more vulnerable than less constrained firms, which leads to Hypothesis 5.1.

[11]The diagram is only a somewhat imaginary way to illustrate a firm's optimization problem. For instance, the MC curve for highly constrained firms is lifted considerably in order to emphasize its nonintersection with the MB curve. This is only for better visualization and does not mean that highly constrained firms must have a sky-high credit spread for the inaction regime to work.

5.2 Hypothesis testing

To empirically test Hypotheses 5.1 and 5.2, one needs only to partition firms by their financial constraints and compare different groups. For instance, one can set up a categorical variable with n equal categories, the most constrained group being the reference category. Replace $\text{FC}_{i,t-1}$ with the categorical in Equation 3.5, and β_1 becomes the coefficient(s) on the following triple interaction.

$$\delta^{-}_{i,t} \times \text{Categorical}_{i,t-1} \times \text{FC}^{peer}_{n,t-1}$$

A FE-DiD regression gives $n-1$ $\beta_{1\,|\,i}$'s because all estimated effects are *relative* to the effect on the reference group (category 0). Denote the estimated relative effect on category i as $\beta^{FE}_{1\,|\,i}$. The relationship between $\beta^{FE}_{1\,|\,i}$'s and $\beta_{1\,|\,i}$'s is given by

$$\beta^{FE}_{1\,|\,i} = \beta_{1\,|\,i} - \beta_{1\,|\,0}, \quad i \in \{1, 2, \cdots, n-1\} \tag{5.3}$$

Although we can never recover $\beta_{1\,|\,i}$ because $\beta_{1\,|\,0}$ is fully absorbed by industry–time fixed effects, knowing $\beta^{FE}_{1\,|\,i}$ is sufficient to distinguish Hypotheses 5.1 and 5.2. Let the highly constrained category be the reference group and subtract $\beta_{1\,|\,\text{Highly constrained}}$ from all terms in Hypothesis 5.1.

$$\begin{aligned}
& \beta_{1\,|\,\text{Highly constrained}} = \beta_{1\,|\,\text{Less constrained}} = 0 \ll \beta_{1\,|\,\text{Unconstrained}} \\
\Longrightarrow\quad & \beta_{1\,|\,\text{Highly}} - \beta_{1\,|\,\text{Highly}} = \beta_{1\,|\,\text{Less}} - \beta_{1\,|\,\text{Highly}} = \ll \beta_{1\,|\,\text{Uncons.}} - \beta_{1\,|\,\text{Highly}} \\
\Longleftrightarrow\quad & 0 = \beta^{FE}_{1\,|\,\text{Less constrained}} \ll \beta^{FE}_{1\,|\,\text{Unconstrained}}
\end{aligned} \tag{5.4}$$

Similarly,

$$\begin{aligned}
& \beta_{1\,|\,\text{Highly constrained}} \ll \beta_{1\,|\,\text{Less constrained}} \le 0 \ll \beta_{1\,|\,\text{Unconstrained}} \\
\Longrightarrow\quad & 0 \ll \beta^{FE}_{1\,|\,\text{Less constrained}} \ll \beta^{FE}_{1\,|\,\text{Unconstrained}}
\end{aligned} \tag{5.5}$$

Therefore, it is possible to examine the existence of crowding out by testing Hypotheses 5.4 and 5.5. If crowding out is rejected, the direction of equilibrium effects will be straightforward.

5.3 Empirical results during downturns

In previous empirical results, the insignificant β_1's for financially constrained firms in either constrained or unconstrained industries (columns (5) to (8) in Tables A.3, A.4, and A.5) already hinted at no significant crowding out because constrained firms do not appear negatively affected by firm interactions.

For a formal test using the method above, I use the text-based measure to construct the categorical $\text{FC}_{i,t-1}$. I set $h = 6$ because it is the most significant period in Figure 3. I explore three versions of $\text{FC}^{peer}_{n,t-1}$ for robustness.

With various levels of granularity, Panels (a) and (b) in Figure 8 test the cross-sectional relative impact of firm interactions in financially constrained industries during industry downturns. Highly constrained firms show no sign of being worse off than less constrained firms.

Meanwhile, unconstrained firms behave significantly different from less constrained firms: in Panel (b), for instance, the average of the two unconstrained categories is significantly higher than the "high" category by 1.11 ($p = 0.041$) and the "less high" category by 1.33 ($p = 0.011$). The results clearly reject the crowding-out hypothesis and do not reject the competitive interaction hypothesis.

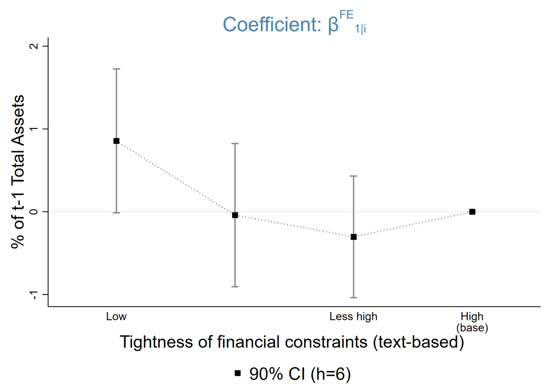
To further rule out the crowding-out hypothesis, I run the same regression but with unconstrained industries. If crowding out were significant, the negative effect on financially constrained firms would be more prominent in unconstrained industries because of higher competition from unconstrained firms. Unconstrained industries are measured by the text-based measure in Panels (c) and (d), and by the ICR in Panels (e) and (f) for robustness. None of them shows any evidence that highly constrained firms are negatively affected.

Finally, because β_1 is primarily driven by small and medium firms, I split firms by size and rerun Figure 8. Estimates for small and medium firms appear in Figure A.3, and results remain unchanged.

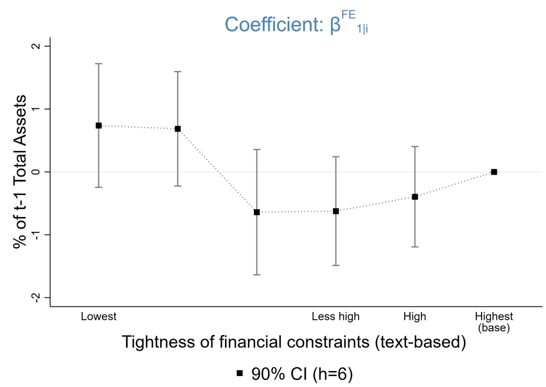
6 Conclusions

In this paper I find that when some firms are financially constrained during industry downturns, their financially unconstrained competitors significantly increase capital expenditure to substitute their depressed investment. The increase is the strongest among unconstrained firms with low or medium market share, and it leads to substantial sales gains in 3-4 years. Empirical findings imply that aggregate effects of financial heterogeneity are significantly mitigated by firm interactions during downturns, a channel that has not been emphasized in the recent macro-finance literature. I also show that competition during negative idiosyncratic shocks is much more intensive than competition during industry downturns. The findings are robust when I replace the financial constraint measure with leverage.

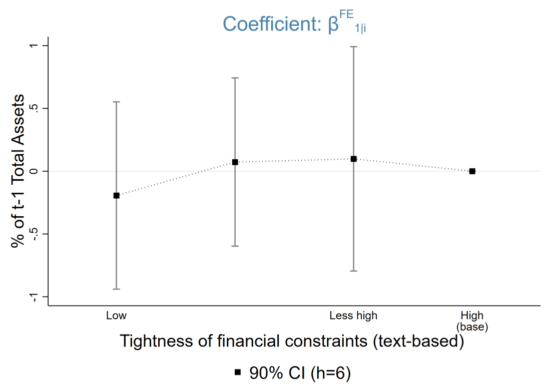
The paper also leaves several open questions for future research. First, in Panel (b) of Figure Figure 5, why are extraordinarily large firms not responsive at all? Ideally, one wants to examine whether they have different strategic considerations, which potentially relates to the discussion of good versus bad concentration by Covarrubias, Gutiérrez, and Philippon (2019); however, this first requires a model much more complicated than the one in Section 5. Second, the sizeable dispersion of financial constraints, which I take as given in this paper, is still less understood. To build a full-scale model to quantify the aggregate effects of this interaction channel, one would first need a thorough investigation into the causes of the profound degree of financial heterogeneity.



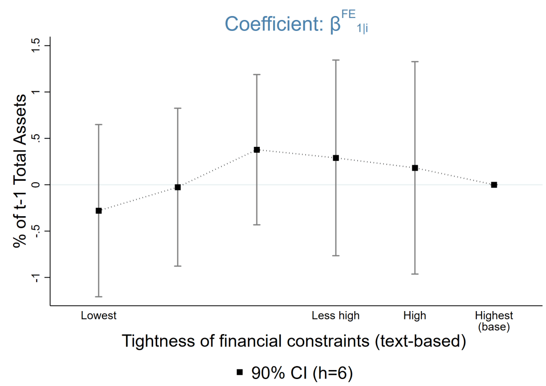
(a) In constrained industries ($n = 4$)



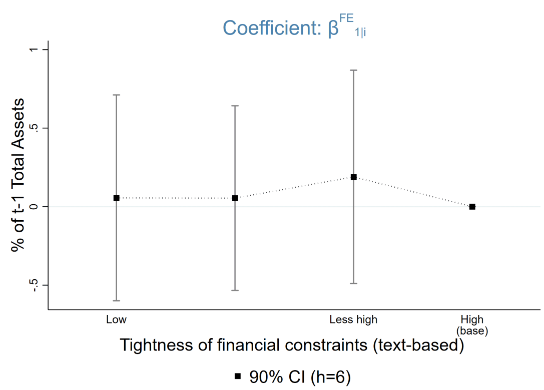
(b) In constrained industries ($n = 6$)



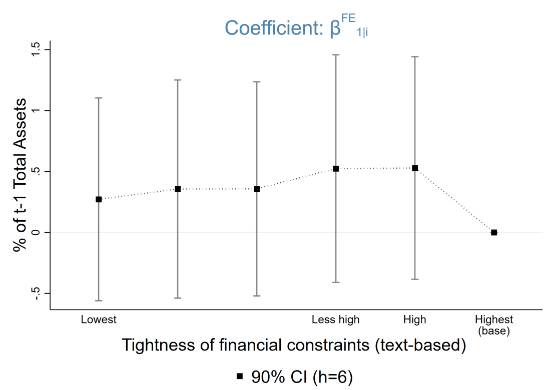
(c) In unconstrained industries ($n = 4$)



(d) In unconstrained industries ($n = 6$)



(e) In high ICR industries ($n = 4$)



(f) In high ICR industries ($n = 6$)

Notes: Estimates of $\beta^{FE}_{1|i}$ are obtained from Equation 3.5. $\text{FC}_{i,t-1}$ is the categorical variable based on the text-based measure, and the number of categories is indicated in panel titles. For $\text{FC}^{peer}_{n,t-1}$, I explore three different versions: unconstrained and constrained industries measured by the text-based measure, and unconstrained industries measured by the ICR.

In Panel (a), the lowest category is higher than the other three categories from left to right by 0.90 ($p = 0.101$), 1.16 ($p = 0.015$), and 0.86 ($p = 0.110$), respectively. In Panel (b), the average of the two lowest categories is higher than the remaining four categories from left to right by 1.35 ($p = 0.041$), 1.33 ($p = 0.011$), 1.11 ($p = 0.041$), and 0.71 ($p = 0.153$), respectively.

Figure 8: Testing Crowding Out ($h = 6$)

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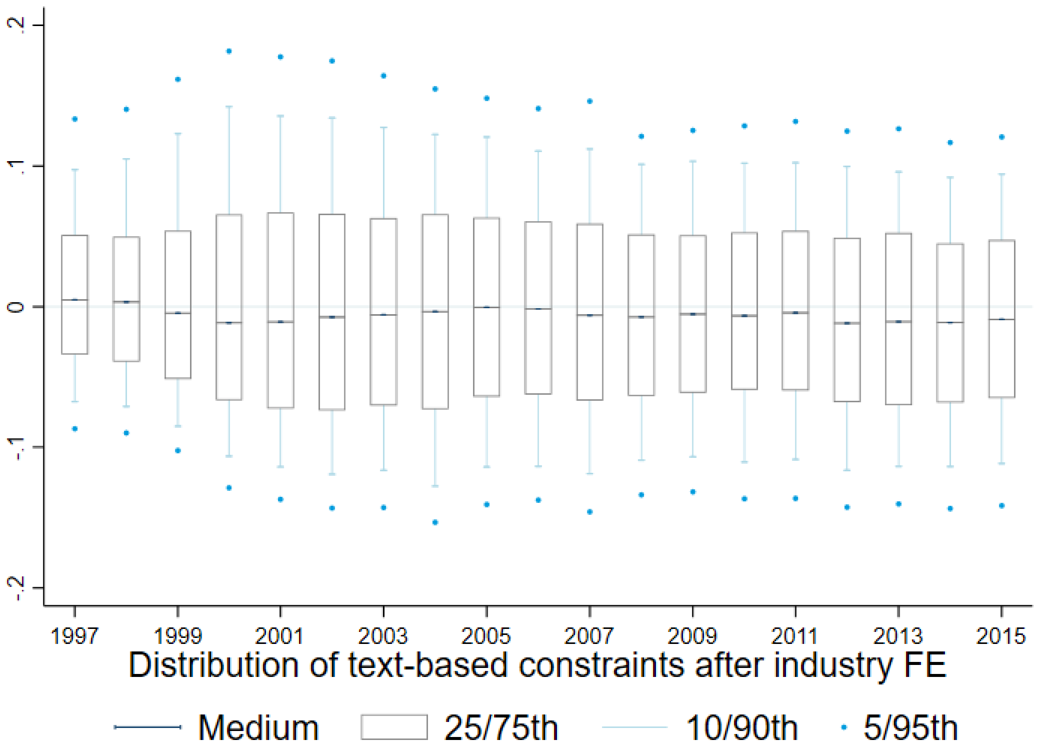
Appendices

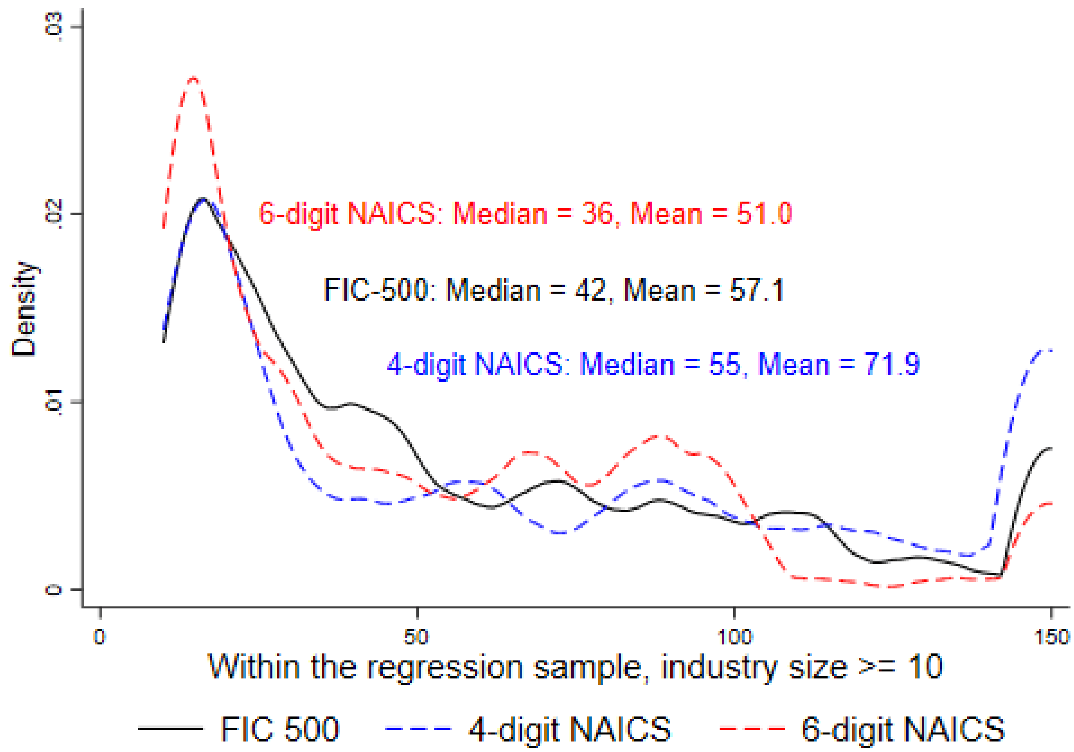
A Additional Tables and Figures

Figure A.1: Dispersion of Financial Constraints



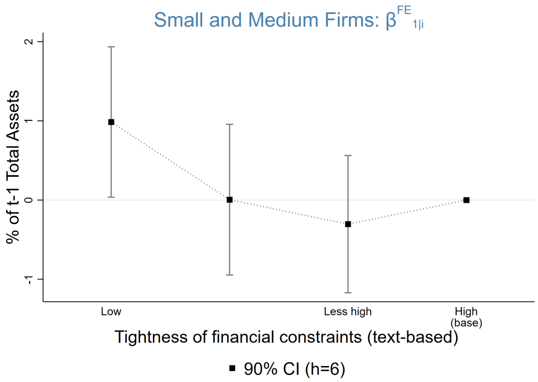
Notes: This figure summarizes the distribution of the text-based financial constraint measure by Hoberg and Maksimovic (2015) after removing industry fixed effects.

Figure A.2: TNIC and NAICS Industry Size Distribution

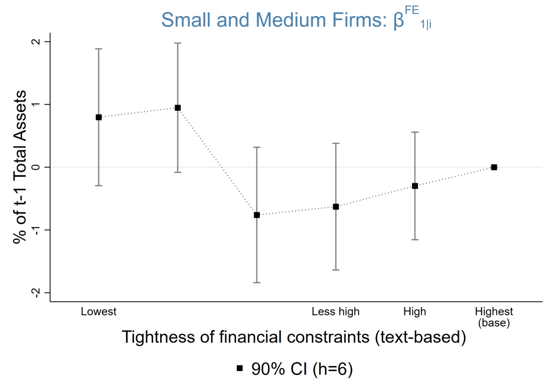


Notes: For comparability, industry sizes in this figure are based on the regression sample with the industry size filter. E.g., if an industry has 100 firms in the entire Compustat database but only 30 firms are included in the regression sample, the industry size would be 30 instead of 100. Comparisons using the whole Compustat sample would be less informative because the regression sample is only a small subset of the Compustat sample.

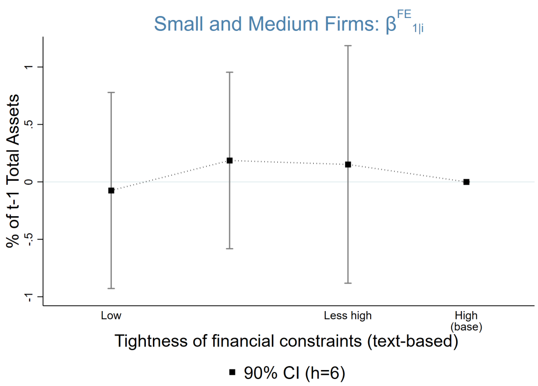
Figure A.3: Testing Crowding Out (Small and Medium Firms, $h = 6$)



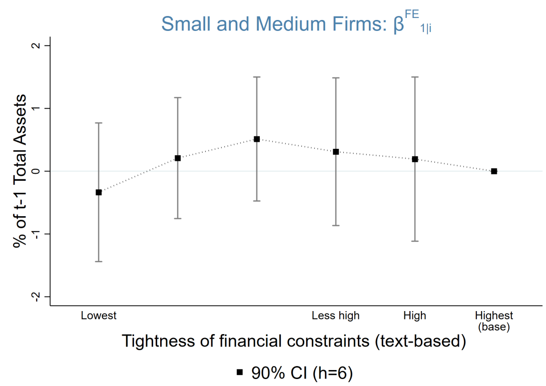
(a) In unconstrained industries ($n = 4$)



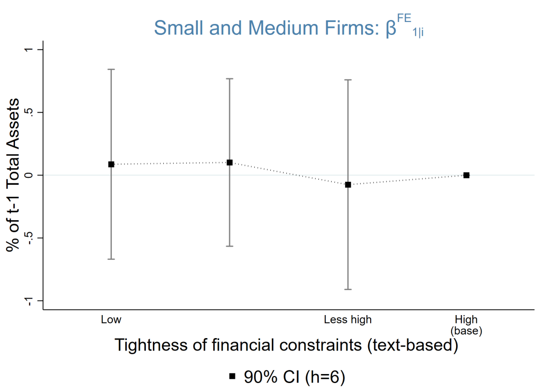
(b) In unconstrained industries ($n = 6$)



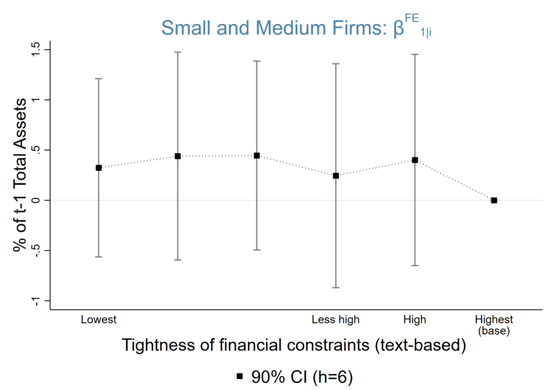
(c) In constrained industries ($n = 4$)



(d) In constrained industries ($n = 6$)



(e) In high ICR industries ($n = 4$)



(f) In high ICR industries ($n = 6$)

Notes: This is the same as Figure 8 except that I split large firms (market share above the 75th percentile) and small and medium firms (market share below the 75th percentile). Here I only show $\beta^{FE}_{1|i}$ for small and medium firms, given that results for large firms are insignificant anyways.

Table A.1: Summary Statistics

	Count	Mean	SD	Min	p25	p50	p75	Max
Sectoral component	126,889	7.43	14.04	-62.50	2.34	8.26	14.32	98.23
Idiosyncratic component	126,889	-0.89	32.97	-189.65	-12.57	-1.16	11.05	168.32
Industry downturns	126,889	0.22	0.41	0.00	0.00	0.00	0.00	1.00
Industry upturns	126,889	0.24	0.43	0.00	0.00	0.00	0.00	1.00
Capital expenditure	126,697	1.32	1.49	0.00	0.35	0.82	1.69	9.96
Unconstrained firm (text-based)	123,665	0.26	0.44	0.00	0.00	0.00	1.00	1.00
Constrained firm (text-based)	123,665	0.26	0.44	0.00	0.00	0.00	1.00	1.00
Unconstrained industry (text-based)	126,889	0.26	0.44	0.00	0.00	0.00	1.00	1.00
Constrained industry (text-based)	126,889	0.21	0.41	0.00	0.00	0.00	0.00	1.00
Leverage	126,762	22.78	22.39	0.00	1.56	18.79	35.74	100.00
Relative leverage	126,762	0.12	19.58	-58.83	-12.49	-4.18	9.38	92.72
Low leverage	126,889	0.22	0.41	0.00	0.00	0.00	0.00	1.00
High leverage	126,889	0.24	0.43	0.00	0.00	0.00	0.00	1.00
ICR below 1	107,169	0.29	0.45	0.00	0.00	0.00	1.00	1.00
Low ICR industry	126,889	0.24	0.42	0.00	0.00	0.00	0.00	1.00
High ICR industry	126,889	0.30	0.46	0.00	0.00	0.00	1.00	1.00
Productivity	123,712	5.44	1.01	-3.09	4.93	5.43	5.97	11.01
Relative productivity	123,712	0.03	0.78	-7.67	-0.32	0.03	0.40	6.02
Market share	126,889	2.73	6.00	0.00	0.10	0.50	2.17	44.99
Tradable sector	126,889	0.64	0.48	0.00	0.00	1.00	1.00	1.00

Notes: Statistics are based on the regression sample with the industry size filter. Productivity refers to labor productivity. Tradable sectors include following 2-digit NAICS industries: 11, 21, 31, 32, 33, 51. The idiosyncratic component is not standardized. Neither the sectoral component nor the idiosyncratic component is winsorized because the input (sales growth) is already winsorized at 2.5 and 97.5 percentiles.

Table A.2: Properties of $\delta_{n,t}$ and $\epsilon_{i,t}$

	(1) Raw Sales Growth	(2) Raw Sales Growth	(3) Idiosyncratic Component	(4) Idiosyncratic Component	(5) Sectoral, AR(1)	(6) Idiosyncratic, AR(1)
Sectoral	0.99***		-0.01**		0.79***	
	(0.01)		(0.01)		(0.00)	
Sectoral x Non-large		1.01***		0.01**		
		(0.01)		(0.01)		
Sectoral x Large		0.90***		-0.10***		
		(0.01)		(0.01)		
Idiosyncratic						0.57***
						(0.00)
Firm FE	Y	Y	Y	Y	Y	Y
Size dummy		Y		Y		
R^2	0.228	0.230	0.109	0.111	0.682	0.407
Within R^2	0.138	0.140	0.000	0.000	0.636	0.331
N	221,255	220,425	221,255	220,425	212,569	212,569
Firms	5,418	5,414	5,418	5,414	5,404	5,404
FIC industries	142	142	142	142	139	139

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The sample includes all observations for which the FIC industry data are available (1988-2019). The size dummy indicates whether a firm's market share exceeds the 75th percentile (2.3%).

Table A.3: Interactions With Financially Constrained Competitors (Text-Based)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Financially unconstrained firms				Financially constrained firms			
	Leverage		Text-based		Leverage		Text-based	
Industry downturns								
Downturn x Dummy	-0.25	-0.12	0.02	0.00	0.16	0.10	-0.21	-0.20
	(0.23)	(0.20)	(0.18)	(0.15)	(0.19)	(0.17)	(0.21)	(0.17)
Downturn x Dummy	1.29**	1.18**	1.01***	0.96***	-0.12	-0.30	-0.26	-0.17
x Constrained peers	(0.57)	(0.51)	(0.36)	(0.30)	(0.40)	(0.38)	(0.41)	(0.31)
Industry upturns								
Upturn x Dummy	-0.21	-0.20	0.01	0.00	0.09	0.08	0.14	0.08
	(0.26)	(0.26)	(0.14)	(0.12)	(0.20)	(0.18)	(0.17)	(0.16)
Upturn x Dummy	0.44	0.37	0.30	0.22	0.26	0.24	-0.50	-0.33
x Constrained peers	(0.39)	(0.36)	(0.35)	(0.28)	(0.32)	(0.31)	(0.30)	(0.25)
Negative idiosyncratic shocks								
Idiosyncratic shocks	-0.88***	-0.84***	-0.86***	-0.83***	-0.87***	-0.83***	-0.88***	-0.83***
	(0.11)	(0.10)	(0.12)	(0.11)	(0.10)	(0.08)	(0.10)	(0.09)
Idio. shocks x Dummy	0.13	0.14	0.00	0.02	0.07	0.06	0.09	0.06
	(0.19)	(0.16)	(0.13)	(0.12)	(0.17)	(0.16)	(0.15)	(0.14)
Idio. shocks x	0.50***	0.43**	0.47***	0.42**	0.52***	0.43***	0.51***	0.46***
Constrained peers	(0.16)	(0.17)	(0.17)	(0.17)	(0.14)	(0.14)	(0.15)	(0.16)
Idio. shocks x Dummy	-0.20	-0.19	0.13	0.03	-0.22	-0.17	-0.11	-0.11
x Constrained peers	(0.21)	(0.20)	(0.24)	(0.20)	(0.24)	(0.23)	(0.20)	(0.19)
Positive idiosyncratic shocks								
Idiosyncratic shocks	0.30***	0.35***	0.28**	0.39***	0.43***	0.48***	0.36***	0.41***
	(0.11)	(0.10)	(0.11)	(0.10)	(0.12)	(0.11)	(0.11)	(0.10)
Idio. shocks x Dummy	0.24	0.27	0.14	-0.03	-0.34	-0.29	-0.19	-0.14
	(0.22)	(0.20)	(0.14)	(0.14)	(0.21)	(0.19)	(0.16)	(0.14)
Idio. shocks x	0.05	-0.06	0.08	-0.10	-0.11	-0.21	-0.07	-0.20
Constrained peers	(0.16)	(0.14)	(0.16)	(0.13)	(0.19)	(0.16)	(0.20)	(0.18)
Idio. shocks x Dummy	-0.31	-0.39	-0.35	-0.20	0.36	0.29	0.28	0.25
x Constrained peers	(0.37)	(0.31)	(0.29)	(0.28)	(0.26)	(0.25)	(0.24)	(0.24)
Other interactions								
Dummy	0.70***	0.74***	-0.00	-0.05	-0.80***	-0.84***	0.19	0.16
	(0.21)	(0.20)	(0.14)	(0.13)	(0.14)	(0.13)	(0.14)	(0.12)
Constrained peers	-0.16	-0.13	-0.50	-0.41	-0.01	0.08	-0.01	-0.07
x Dummy	(0.32)	(0.33)	(0.33)	(0.29)	(0.28)	(0.27)	(0.28)	(0.26)
FIC, Firm, Time FE	Y	Y	Y	Y	Y	Y	Y	Y
FIC x Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry size	Y	Y	Y	Y	Y	Y	Y	Y
Full interaction controls	Y	Y	Y	Y	Y	Y	Y	Y
GFC period		Y		Y		Y		Y
R^2	0.735	0.728	0.734	0.726	0.735	0.728	0.734	0.726
Within R^2	0.132	0.136	0.133	0.136	0.133	0.136	0.133	0.136
N	95,112	112,990	92,869	110,455	95,112	112,990	92,869	110,455
Firms	4,208	4,272	4,052	4,111	4,208	4,272	4,052	4,111
FIC industries	95	96	95	96	95	96	95	96

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the cumulative CAPX in 6 quarters ($h = 6$). Financially constrained competitors are identified using the text-based measure. In the first four columns, $FC_{i,t-1}$ is a dummy for financially unconstrained firms, whereas in the last four columns, $FC_{i,t-1}$ is a dummy for financially constrained firms. The header indicates whether it uses the leverage-based or text-based measure.

Table A.4: Interactions With Financially Unconstrained Competitors (Text-Based)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Financially unconstrained firms				Financially constrained firms			
	Leverage		Text-based		Leverage		Text-based	
Industry downturns								
Downturn x Dummy	0.11	0.22	0.26	0.24	0.12	0.01	-0.33*	-0.25
	(0.28)	(0.25)	(0.20)	(0.15)	(0.19)	(0.18)	(0.18)	(0.15)
Downturn x Dummy	-0.23	-0.20	-0.37	-0.35	-0.04	0.04	0.11	-0.09
x Unconstrained peers	(0.36)	(0.31)	(0.28)	(0.23)	(0.30)	(0.28)	(0.41)	(0.35)
Industry upturns								
Upturn x Dummy	-0.05	-0.06	0.08	0.04	0.27	0.24	-0.18	-0.13
	(0.23)	(0.22)	(0.16)	(0.13)	(0.18)	(0.17)	(0.16)	(0.15)
Upturn x Dummy	-0.05	-0.14	-0.04	-0.05	-0.40	-0.31	0.52	0.37
x Unconstrained peers	(0.38)	(0.35)	(0.34)	(0.31)	(0.42)	(0.37)	(0.57)	(0.53)
Negative idiosyncratic shocks								
Idiosyncratic shocks	-0.61***	-0.61***	-0.58***	-0.57***	-0.58***	-0.59***	-0.64***	-0.61***
	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.13)
Idio. shocks x Dummy	0.04	0.07	-0.07	-0.07	-0.06	-0.02	0.13	0.07
	(0.14)	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.09)	(0.08)
Idio. shocks x	-0.27	-0.26	-0.39*	-0.37*	-0.32*	-0.30*	-0.22	-0.24
Unconstrained peers	(0.20)	(0.19)	(0.21)	(0.20)	(0.19)	(0.18)	(0.19)	(0.19)
Idio. shocks x Dummy	-0.05	-0.07	0.27	0.27	0.17	0.13	-0.35	-0.15
x Unconstrained peers	(0.28)	(0.26)	(0.25)	(0.22)	(0.25)	(0.26)	(0.42)	(0.37)
Positive idiosyncratic shocks								
Idiosyncratic shocks	0.29***	0.30***	0.28***	0.31***	0.33***	0.32***	0.30***	0.31***
	(0.08)	(0.07)	(0.08)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)
Idio. shocks x Dummy	-0.01	-0.05	0.04	-0.06	-0.12	-0.09	-0.04	-0.03
	(0.25)	(0.22)	(0.15)	(0.13)	(0.15)	(0.15)	(0.10)	(0.10)
Idio. shocks x	0.18	0.20	0.21	0.25	0.31	0.37*	0.29	0.33*
Unconstrained peers	(0.20)	(0.19)	(0.24)	(0.22)	(0.22)	(0.20)	(0.21)	(0.20)
Idio. shocks x Dummy	0.41	0.54	0.03	0.11	-0.25	-0.30	-0.65	-0.53
x Unconstrained peers	(0.38)	(0.35)	(0.33)	(0.30)	(0.32)	(0.31)	(0.42)	(0.39)
Other interactions								
Dummy	0.73***	0.78***	-0.19	-0.18	-0.84***	-0.88***	0.21	0.17
	(0.22)	(0.21)	(0.16)	(0.15)	(0.14)	(0.15)	(0.13)	(0.12)
Unconstrained peers	-0.24	-0.21	0.44*	0.34*	0.16	0.16	-0.19	-0.17
x Dummy	(0.25)	(0.24)	(0.23)	(0.20)	(0.18)	(0.18)	(0.27)	(0.25)
FIC, Firm, Time FE	Y	Y	Y	Y	Y	Y	Y	Y
FIC x Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry size	Y	Y	Y	Y	Y	Y	Y	Y
Full interaction controls	Y	Y	Y	Y	Y	Y	Y	Y
GFC period		Y		Y		Y		Y
R^2	0.735	0.727	0.734	0.725	0.735	0.727	0.734	0.725
Within R^2	0.130	0.133	0.130	0.133	0.131	0.133	0.130	0.133
N	95,112	112,990	92,869	110,455	95,112	112,990	92,869	110,455
Firms	4,208	4,272	4,052	4,111	4,208	4,272	4,052	4,111
FIC industries	95	96	95	96	95	96	95	96

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the cumulative CAPX in 6 quarters ($h = 6$). Financially unconstrained competitors are identified using the text-based measure.

Table A.5: Interactions With High ICR Competitors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Financially unconstrained firms				Financially constrained firms			
	Leverage		Text-based		Leverage		Text-based	
Industry downturns								
Downturn x Dummy	0.09	0.23	0.28*	0.21	0.08	-0.04	-0.34*	-0.22
	(0.26)	(0.23)	(0.16)	(0.14)	(0.19)	(0.17)	(0.18)	(0.16)
Downturn x Dummy x High ICR peers	-0.55*	-0.52*	-0.45*	-0.22	0.21	0.22	0.27	-0.13
	(0.31)	(0.27)	(0.24)	(0.23)	(0.27)	(0.24)	(0.28)	(0.25)
Industry upturns								
Upturn x Dummy	-0.02	-0.02	0.17	0.13	0.13	0.14	-0.17	-0.15
	(0.23)	(0.23)	(0.14)	(0.13)	(0.19)	(0.19)	(0.17)	(0.17)
Upturn x Dummy x High ICR peers	-0.20	-0.27	-0.36	-0.32	0.34	0.26	0.12	0.20
	(0.36)	(0.32)	(0.25)	(0.20)	(0.30)	(0.28)	(0.33)	(0.31)
Negative idiosyncratic shocks								
Idiosyncratic shocks	-0.58***	-0.59***	-0.54***	-0.54***	-0.55***	-0.56***	-0.60***	-0.58***
	(0.13)	(0.14)	(0.13)	(0.14)	(0.13)	(0.13)	(0.12)	(0.13)
Idio. shocks x Dummy	0.06	0.08	-0.10	-0.10	-0.06	-0.03	0.10	0.06
	(0.13)	(0.12)	(0.12)	(0.11)	(0.13)	(0.12)	(0.09)	(0.08)
Idio. shocks x High ICR peers	-0.31*	-0.23	-0.40**	-0.30*	-0.42**	-0.29*	-0.43**	-0.33*
	(0.17)	(0.17)	(0.17)	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)
Idio. shocks x Dummy x High ICR peers	-0.20	-0.13	0.13	0.11	0.23	0.10	0.35	0.26
	(0.29)	(0.23)	(0.28)	(0.24)	(0.27)	(0.21)	(0.25)	(0.22)
Positive idiosyncratic shocks								
Idiosyncratic shocks	0.36***	0.37***	0.34***	0.36***	0.39***	0.38***	0.38***	0.36***
	(0.08)	(0.08)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.09)
Idio. shocks x Dummy	-0.03	-0.07	0.02	-0.07	-0.13	-0.09	-0.07	-0.03
	(0.25)	(0.22)	(0.15)	(0.13)	(0.17)	(0.16)	(0.10)	(0.09)
Idio. shocks x High ICR peers	-0.19	-0.13	-0.16	-0.10	-0.06	0.04	-0.11	0.01
	(0.18)	(0.16)	(0.20)	(0.17)	(0.19)	(0.17)	(0.20)	(0.17)
Idio. shocks x Dummy r x High ICR peers	0.52	0.55	0.13	0.19	-0.18	-0.27	-0.11	-0.29
	(0.40)	(0.34)	(0.31)	(0.27)	(0.31)	(0.30)	(0.26)	(0.23)
Other interactions								
Dummy	0.70***	0.76***	-0.08	-0.08	-0.78***	-0.82***	0.19	0.11
	(0.22)	(0.21)	(0.14)	(0.12)	(0.14)	(0.15)	(0.14)	(0.12)
High ICR peers x Dummy	-0.04	-0.06	0.07	0.01	-0.13	-0.07	-0.05	0.07
	(0.19)	(0.18)	(0.16)	(0.15)	(0.15)	(0.14)	(0.18)	(0.16)
FIC, Firm, Time FE	Y	Y	Y	Y	Y	Y	Y	Y
FIC x Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry size	Y	Y	Y	Y	Y	Y	Y	Y
Full interaction controls	Y	Y	Y	Y	Y	Y	Y	Y
GFC period		Y		Y		Y		Y
R^2	0.734	0.726	0.733	0.725	0.734	0.726	0.733	0.725
Within R^2	0.128	0.132	0.128	0.131	0.128	0.132	0.128	0.131
N	95,112	112,990	92,869	110,455	95,112	112,990	92,869	110,455
Firms	4,208	4,272	4,052	4,111	4,208	4,272	4,052	4,111
FIC industries	95	96	95	96	95	96	95	96

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the cumulative CAPX in 6 quarters ($h = 6$).

Table A.6: Medium-Term Gains in Sales

	(1)	(2)	(3)	(4)	(5)
	Financially unconstrained x Small / medium				
	h=4	h=8	h=12	h=16	h=20
Industry downturns					
Downturn x Dummy	0.48	0.87	-0.09	-0.79	-1.80
	(0.91)	(1.48)	(1.78)	(2.07)	(2.50)
Downturn x Dummy x Constrained peers	0.83	3.32	5.42	9.88*	10.91*
	(1.68)	(2.87)	(3.91)	(5.13)	(6.40)
Industry upturns					
Upturn x Dummy	0.05	-0.59	-0.89	-2.90	-5.26**
	(0.82)	(1.26)	(1.66)	(2.04)	(2.62)
Upturn x Dummy x Constrained peers	2.88*	3.98*	4.68	5.45	7.71
	(1.46)	(2.27)	(3.03)	(4.08)	(5.57)
Negative idiosyncratic shocks					
Idiosyncratic shocks	-12.13***	-11.31***	-10.76***	-9.95***	-9.35***
	(0.81)	(1.01)	(1.07)	(1.21)	(1.51)
Idio. shocks x Dummy	-1.64**	-2.30**	-2.31	-4.26**	-4.18*
	(0.68)	(1.04)	(1.65)	(1.94)	(2.36)
Idio. shocks x Constrained peers	6.43***	5.87***	6.33***	4.90**	3.67
	(1.80)	(1.81)	(2.16)	(2.39)	(2.76)
Idio. shocks x Dummy x Constrained peers	0.36	0.64	0.63	4.38	4.31
	(1.06)	(1.83)	(2.71)	(3.70)	(4.14)
Positive idiosyncratic shocks					
Idiosyncratic shocks	9.64***	9.08***	9.12***	9.87***	9.93***
	(0.62)	(0.91)	(1.14)	(1.38)	(1.67)
Idio. shocks x Dummy	0.49	0.90	-0.02	-2.00	-3.32
	(0.94)	(1.36)	(1.73)	(2.06)	(2.51)
Idio. shocks x Constrained peers	-5.01***	-4.23**	-3.86**	-5.70***	-5.78**
	(1.36)	(1.62)	(1.58)	(2.06)	(2.31)
Idio. shocks x Dummy x Constrained peers	0.73	-0.12	-0.02	3.98	6.14
	(1.57)	(2.28)	(2.67)	(3.42)	(4.54)
Other interactions					
Dummy	0.59	1.59	3.71**	5.48***	7.32***
	(0.59)	(1.04)	(1.57)	(2.02)	(2.71)
Constrained peers x Dummy	-1.14	-0.66	-1.31	-4.02	-3.83
	(1.21)	(1.92)	(2.55)	(3.20)	(4.78)
FIC, Firm, Time FE	Y	Y	Y	Y	Y
FIC x Time FE	Y	Y	Y	Y	Y
Industry size	Y	Y	Y	Y	Y
Full interaction controls	Y	Y	Y	Y	Y
GFC period	Y	Y	Y	Y	Y
R^2	0.490	0.531	0.574	0.612	0.645
Within R^2	0.147	0.087	0.070	0.064	0.060
N	94,448	94,264	94,350	95,024	86,425
Firms	3,675	3,672	3,675	3,691	3,414
FIC industries	95	95	95	95	95

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the change in future sales as defined in Equation 4.1. The sample is restricted to firms with non-missing $\text{Sales}_{i,t+16}$. The firm dummy indicates firms that are both financially unconctrained and with market share below the 75th percentile. Coefficients associated with large firms are not reported for simplicity.

B Shock Decomposition

B.1 Decomposition under CES and monopolistic competition

Here I derive a simple shock decomposition method following di Giovanni, Levchenko, and Mejean (2014). Because I use only one country, I can drop the country dimension. The economy has a large number of sectors, indexed by $j \in \{1, \cdots, J\}$. A large number of firms are indexed by $f \in \mathscr{S}$.

The demand side is Cobb-Douglas with time-varying sectoral demand shock $\phi_{j,t}$.

$$U_t = \Pi_{j=1}^{J} \left(Y_{j,t}\right)^{\phi_{j,t}} \tag{B.1}$$

$Y_{j,t}$ is the sectoral output, which is a CES aggregate of firm output $y_{f,t}$,

$$Y_{j,t} = \left[\sum_{i \in \mathscr{S}} \omega_{f,t}^{\frac{1}{\theta}} y_{f,t}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \tag{B.2}$$

where θ is the elasticity of substitution and $\omega_{f,t}$ is a firm-specific demand shock.

Define $p_{f,t}$ as the firm-specific price and $P_{j,t}$ as the sectoral price index. Let κ_t be the Lagrangian multiplier of the budget constraint; then we have

$$\begin{aligned} p_{f,t} &= \frac{U_t}{\kappa_t} \phi_{j,t} \omega_{f,t}^{\frac{1}{\theta}} Y_{j,t}^{\frac{1}{\theta}-1} y_{f,t}^{-\frac{1}{\theta}} \\ &= P_{j,t} \omega_{f,t}^{\frac{1}{\theta}} \left(\frac{Y_{j,t}}{y_{f,t}}\right)^{\frac{1}{\theta}}. \end{aligned} \tag{B.3}$$

On the production side suppose that firms have a linear production function with only one input (because I do only a static model, including capital costs does not change the results).

$$y_{f,t} = A_{f,t} l_{f,t} \tag{B.4}$$

Firms take the nominal input cost w_t as given and maximize one-period profit π_i

$$\max_{l_{f,t}} p_{f,t} y_{f,t} - w_t l_{f,t} = \max_{l_{f,t}} P_{j,t} \omega_{f,t}^{\frac{1}{\theta}} \left(\frac{Y_{j,t}}{y_{f,t}}\right)^{\frac{1}{\theta}} y_{f,t} - \frac{w_t}{A_{f,t}} y_{f,t} \tag{B.5}$$

The first-order condition is

$$\frac{w_t}{A_{f,t}} = P_{j,t} \omega_{f,t}^{\frac{1}{\theta}} Y_{j,t}^{\frac{1}{\theta}} \left(1 - \frac{1}{\theta}\right) y_{f,t}^{-\frac{1}{\theta}} \tag{B.6}$$

so that

$$
\begin{aligned}
y_{f,t}^{\frac{1}{\theta}} &= \frac{A_{f,t}}{w_t} P_{j,t} \omega_{f,t}^{\frac{1}{\theta}} Y_{j,t}^{\frac{1}{\theta}} \left(1 - \frac{1}{\theta}\right) \\
p_{f,t} &= \frac{w_t}{A_{f,t}} \frac{\theta}{\theta - 1}
\end{aligned}
\tag{B.7}
$$

and a firm's sales are

$$
\begin{aligned}
p_{f,t} y_{f,t} &= P_{j,t}^{\theta} \omega_{f,t} Y_{j,t} \left(\frac{w_t}{A_{f,t}} \frac{\theta}{\theta - 1} \right)^{1-\theta} \\
&= P_{j,t}^{\theta-1} \omega_{f,t} \phi_{j,t} Y_t \left(\frac{w_t}{A_{f,t}} \frac{\theta}{\theta - 1} \right)^{1-\theta} .
\end{aligned}
\tag{B.8}
$$

The second equality derives from the fact that in equilibrium the utility function ensures that $\phi_{j,t}$ is the expenditure share of $P_{j,t} Y_{j,t}$ in total income Y_t.

From above, $\ln\left(p_{f,t} y_{f,t}\right)$ is clearly a linear combination of (1) macro factors indexed by t (w_t and Y_t), (2) sectoral factors indexed by $\{j, t\}$ ($P_{j,t}$, $Y_{j,t}$, $\phi_{j,t}$), and (3) firm-level idiosyncratic factors indexed by $\{f, t\}$ ($\omega_{f,t}$ and $A_{f,t}$). Hence, using Equation 3.3 to separate sectoral factors (or macro sectoral factors) and idiosyncratic factors is feasible. For our purposes, further separating macro factors and sectoral factors is unnecessary because macro factors are fully absorbed by time fixed effects.

B.2 Decomposition under imperfect competition

As discussed in Section 3, this method is empirically biased (also see Yeh, 2017), but several alternative frameworks are available. Many theoretical papers have explored VES models of monopolistic competition (e.g., Kimball, 1995, Zhelobodko et al., 2012). Atkeson and Burstein (2008), Amiti, Itskhoki, and Konings (2019), and Wang and Werning (2022) study oligopolistic models with empirical applications.

To understand potential biases brought by imperfect competition, I augment the previous model with imperfect competition and differentiated elasticity of substitution. I drop the firm-specific demand shock ω_f because it is indistinguishable from A_f in this framework. I also drop t to simplify notation.

Environment. Assume that a product market j has n large firms, $\{L_{1,j}, \cdots, L_{n,j}\}$, as well as a continuum of fringe firms competing à la Cournot. Firms in the fringe $\mathscr{F}_j$ can be summed up as a synthetic firm, F_j. Then we have a synthetic set of $n+1$ firms in the market:

$$
\mathscr{S}_j = \{L_{1,j}, L_{2,j}, \cdots, L_{n,j}, F_j\} \tag{B.9}
$$

Large firms produce differentiated products and, therefore, have firm-specific elasticities (θ_f). The synthetic fringe firm also has an elasticity parameter θ with $\theta_f > \theta$. The aggregate output is given by

$$Y_j = \left[\sum_{f\in\mathscr{S}} y_f^{\frac{\theta_f-1}{\theta_f}}\right]^{\frac{\theta}{\theta-1}}, \quad \text{where if } f\in F_j,\ \theta_f=\theta \tag{B.10}$$

where y_f is the output of each firm. Note that if only fringe firms but no large firms exist, then the aggregator B.10 becomes a standard CES aggregator.

Demand. The demand side remains the same.

$$U = \Pi_{j=1}^{J}\left(Y_j\right)^{\phi_j} \tag{B.11}$$

Let κ_t be the Lagrangian multiplier of the budget constraint and $P_{j,t}$ be the sectoral price index. We have

$$p_f = \frac{U}{\kappa}\phi_j\frac{\theta}{\theta-1}\frac{\theta_f-1}{\theta_f}\times Y_j^{\frac{1}{\theta}-1}y_f^{-\frac{1}{\theta_f}} \tag{B.12}$$

To keep the problem tractable, I assume that large firms can affect industry-level output Y_j but not national variables (U and κ).

Supply. The supply side is the same, except that now $\frac{\partial Y_j}{\partial y_f}\neq 0$.

$$\begin{aligned}\max_{l_f}\ p_f y_f - w_t l_f &= \max_{l_f}\frac{U}{\kappa}\frac{\theta}{\theta-1}\times\phi_j\frac{\theta_f-1}{\theta_f}\times Y_j^{\frac{1}{\theta}-1}y_f^{1-\frac{1}{\theta_f}}-\frac{w_t}{A_f}y_f\\ &=\max_{l_f}\frac{U}{\kappa}\frac{\theta}{\theta-1}\times\phi_j\frac{\theta_f-1}{\theta_f}\times\left[\sum_{f\in\mathscr{S}}y_f^{\frac{\theta_f-1}{\theta_f}}\right]^{-1}y_f^{\frac{\theta_f-1}{\theta_f}}-\frac{w_t}{A_f}y_f\end{aligned} \tag{B.13}$$

The first-order condition is

$$\begin{aligned}\frac{w_t}{A_f} &= \frac{U}{\kappa}\frac{\theta}{\theta-1}\times\phi_j\left(\frac{\theta_f-1}{\theta_f}\right)^2\times\left[\sum_{f\in\mathscr{S}}y_f^{\frac{\theta_f-1}{\theta_f}}\right]^{-1}y_f^{-\frac{1}{\theta_f}}\\ &-\frac{U}{\kappa}\frac{\theta}{\theta-1}\times\phi_j\left(\frac{\theta_f-1}{\theta_f}\right)^2\times\left[\sum_{f\in\mathscr{S}}y_f^{\frac{\theta_f-1}{\theta_f}}\right]^{-2}y_f^{\frac{\theta_f-2}{\theta_f}}\end{aligned} \tag{B.14}$$

which can be written as

$$\frac{w_t}{A_f} = p_f\frac{\theta_f-1}{\theta_f}\left[1-\frac{y_f^{1-\frac{1}{\theta_f}}}{Y_j^{1-\frac{1}{\theta}}}\right] \tag{B.15}$$

Implications. Define the real market share Γ_f as follows. Either a high θ_f or a high y_f can lead to a high Γ.

$$\Gamma_f = \frac{y_f^{1-\frac{1}{\theta_f}}}{Y_j^{1-\frac{1}{\theta}}} \tag{B.16}$$

Of course, Γ_f is an endogenous variable, but it still helps to understand the optimal price p_f. The supply curve B.15 indicates that a firm with a larger real market share Γ_f can charge a higher price.

$$p_f = \frac{w_t}{A_f}\frac{\theta_f}{\theta_f - 1}\frac{1}{1-\Gamma_f} \tag{B.17}$$

The demand curve B.12 specifies that for the same price, demand is stronger for firms with larger market shares.

$$p_f = \frac{U}{\kappa}\phi_j\frac{\theta}{\theta-1}\frac{\theta_f - 1}{\theta_f} \times \Gamma_f \times y_f^{-1} \tag{B.18}$$

How does a ϕ_j shock change the system? Here I re-write the demand curve in the log form.

$$\ln\left(p_f y_f\right) = \ln\phi_j + \ln\Gamma_f + \ln\frac{U}{\kappa} + \ln\frac{\theta_f - 1}{\theta_f} + \ln\frac{\theta}{\theta-1} \tag{B.19}$$

Although it looks similar to the monopolistic case (Equation B.8), in which $\ln\phi_j$ can be easily separated from the rest, in the imperfect case Γ_f is endogenous and thus a function of ϕ_j; so the previous decomposition is no longer correct. How does Γ_f respond to ϕ_j shocks? Intuitively, larger firms have higher margins and, therefore, more room to adjust; so their market shares should be countercyclical: the higher the θ_f, the more negative the correlation between Γ_f and ϕ_j. The revenue elasticity to sectoral demand is, therefore, decreasing in θ_f.

In short, I show that firms' responses to the sectoral shock ϕ_j is also affected by the real market share Γ_f and, therefore, θ_f. In industries where market shares are highly uneven, the simple decomposition method will be biased.

PUBLICATIONS

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