Financial Constraints and Price Rigidities

Yang Liu [*]
Boston College

May 24, 2025

Abstract

I show that binding financial constraints undermine price rigidities both theoretically and empirically. After negative shocks, financially constrained firms have to improve cash flows through internal earnings, hence they move closer to the flexible price path that maximizes internal cash flows despite intertemporal trade-offs due to nominal rigidities. Financially constrained firms also exhibit little strategic complementarities in pricing, as they heavily discount the cost of losing customers to competitors in the future. In aggregate, this "price rigidity" channel creates non-linearity in the Phillips curve. When large shocks tighten financial constraints by eroding profitability, prices become more flexible, and the Phillips curve becomes steeper. Lower price rigidities, particularly during large shocks, substantially amplify inflation dynamics and destabilize the macroeconomy.

JEL classification: E31, E52, G32
Keywords: Inflation, price rigidities, financial constraints, Phillips curve

1 Introduction

Since the seminal work by Chevalier and Scharfstein (1996), a vast literature has found evidence that financial constraints affect firms' optimal prices. While *prices* are important macroeconomic phenomena, *price rigidities* are at least equally important because they are the fundamental friction in the New Keynesian framework. Therefore in this paper, I study how financial constraints affect *price rigidities* and what the macroeconomic implications are.

Why should financial constraints affect price rigidities? The intuition is straightforward even in a minimalist model with only nominal rigidities and financial frictions. Financial constraints alter the intertemporal trade-offs between current and future cash flows. Such alterations weaken the role of nominal rigidities because nominal rigidities effect through the very same intertemporal trade-offs. In the textbook New Keynesian model, a firm attains maximal

[*]Email: yang.liu.7@bc.edu. I thank Susanto Basu, Damien Capelle, Gabriel Chodorow-Reich, Pablo Guerron, Jaromir Nosal, Fabio Schiantarelli, Rosen Valchev, and seminar participants at the 2024 EEA conference, 2024 Green Line Macro Meeting, 2025 Brown University PhD conference for helpful comments.

internal cash flows (equivalent to EBITDA[1] in simple models) in each period along the optimal flexible price path. Since the sticky price path generally differs from the flexible price path, EBITDA along the sticky price path is below the flexible price level in each period. While a firm can improve current EBITDA by setting current prices closer to flexible prices, the optimality condition means that such an attempt must lower future profits by more. Financial constraints, however, alter this intertemporal optimality. If a firm is pushed towards illiquidity in a recession and external financing is constrained, it has to raise its current EBITDA to improve cash flows. In this case, the firm will set prices closer to the flexible price path whenever possible at the expense of future profits, resulting in lower observed price rigidities. Therefore, I refer to this channel as the "price rigidity" channel hereafter.

My theoretical model also makes distinct predictions on how financial constraints interact with strategic complementarities, an important form of real rigidities. If a firm's demand elasticity is affected by the contemporaneous prices set by its competitors, financially constrained firms should react more to competitors' prices compared to unconstrained firms. This applies to usual static demand models such as Atkeson and Burstein (2008). The intuition is that, if financially constrained firms prioritize current EBITDA, they should prioritize any factor that affects its current EBITDA including competitors' prices. By contrast, if demand elasticity is affected by competitors' prices but with a lag, financially constrained firms should react less and exhibit lower strategic complementarities. The latter case applies to models where strategic complementarities come from dynamic demand elasticity. For a simple example of the latter, imagine a model where it takes time for customers to switch to other sellers. A financially constrained firm would therefore choose to raise markups to maximize its short-run EBITDA before customers switch away, even knowing that it will lose customers to its competitors in the long run. By empirically testing the model, one can discriminate between the two ways of modeling strategic complementarities.

To empirically test my model predictions, I use the Indian Prowess database, which collects product-level input and output prices as well as firm-level financial statements for Indian manufacturing firms. The unique availability of price and financial variables makes it ideal to test my model. My empirical strategy builds on the framework in Amiti et al. (2019), who regress prices on a firm's own marginal cost and its competitors' prices to estimate the pricing function. On top of that, I interact both terms with financial constraints. The pass-through of the marginal cost over time informs the degree of nominal rigidities, the sensitivity to competitors' prices informs the degree of strategic complementarities, and the interaction terms tell how financially constrained firms set prices differently. While financial constraints cannot be measured directly in the data, I explore three proxies. First, given the pivotal role of internal cash flows in the theoretical model, I use the lagged EBITDA-to-sales ratio that directly measures the availability of internal cash flows. In addition, I use the interest coverage ratio (ICR) and the debt service coverage ratio (DSCR), each capturing a different aspect of indebtedness, as proxies for financial constraints.[2]

[1] Earnings before interest, taxes, depreciation, and amortization. In the model used in this paper, EBITDA, operating profits, and internal cash flows are all identical, and I use them interchangeably.

[2] The two ratios are also superior to the leverage ratio, another commonly used ratio in the literature. Even for firms with the same leverage ratio, their financial health can still differ substantially depending on their cost of debt (captured by the ICR) and their maturity structure (captured by the DSCR). See Section 3.1.4.

Across all three different measures, I find that financial constraints have significant and sizable effects on price rigidities. First, consistent with the theory, financially constrained firms attain a pass-through rate of 88% within one year after marginal cost shocks, while financially unconstrained firms pass only 65% of the marginal cost into prices. Second, the interaction between financial constraints and price rigidities exhibits high nonlinearity. After large cost increases, the pass-through rate of constrained firms reaches almost 100%, whereas unconstrained firms barely change their pass-through rate. The sharp contrast also proves that the nonlinearity does not result from state-dependent pricing typically found in menu-cost models. Third, by moving closer to complete pass-through, financially constrained firms show smaller decreases in profit margins, which further confirms my theory. Importantly, firms show no noticeable difference in their current and future input prices, suggesting that my results are not confounded by heterogeneity on the cost side.

Second, I examine the dynamic aspect of the price rigidity channel. After an initial input price shock, input prices decline by over 30% in one year and 40% in two years. For financially unconstrained firms, price responses are smooth and persistent over time. Their prices remain unchanged after one year and only start to decline after two years. Such timing is the *prima facie* evidence on price stickiness. By contrast, financially constrained firms substantially revise prices downwards after one year as costs revert, such that the pass-through gap between constrained and unconstrained firms completely closes after one year. This pattern confirms that constrained firms behave more like flexible-price firms and that the difference in initial price responses is not driven by any permanent heterogeneity in their pricing functions.

Interestingly, financially constrained firms display no significant strategic complementarities, whereas unconstrained firms respond significantly to competitors' prices with an elasticity of 35%. In other words, financially constrained firms show not only weaker *nominal rigidities* but also weaker *real rigidities*. Through the lens of my theoretical model, this pattern is consistent with a model with dynamic demand elasticity, such that higher relative prices today increase future but not current demand elasticity. Note that this is also qualitatively consistent with the intuition in Gilchrist et al. (2017). The latter embeds customer bases and imperfect capital markets in a New Keynesian model, which incentivizes firms to lower markups to invest in their customer bases in normal times. Yet after some shocks such as credit shocks, financially constrained firms have to raise markup to improve cash flows at the expense of future customer bases, resulting in positive markup shocks and higher prices. Strictly speaking, the model in Gilchrist et al. (2017) has no strategic complementarities, yet the intuition is well aligned with my empirical findings.

What are the implications for inflation dynamics and the Phillips curve? To understand the macro consequences, I embed earnings-based borrowing constraints in a textbook New Keynesian model. The model also features a continuum of heterogeneous firms to smooth out the kink induced by occasionally binding constraints at the firm level. I calibrate the benchmark model using standard parameter values, and the benchmark model generates similar nonlinearity as in the empirical analysis. For comparison, I also construct a financially unconstrained model, which is identical to the benchmark model except that financial constraints never bind. The two models differ substantially in terms of linearity. After a small negative shock, the benchmark model behaves similar to the unconstrained model. After a large negative shock, inflation in the benchmark model is amplified by 15% compared to the linear extrapolation of results after a small shock. Moreover, the larger is the shock, the higher is the amplification. By contrast, the unconstrained model after a large shock is almost identical to the linear extrapolation of the same model after a small shock.

The benchmark model also differs in other important aspects. First, the nonlinear inflation dynamics smooth markup fluctuations in a more realistic way. In the unconstrained model, average markup may even fall below zero if the shock is large enough, yet it is highly counterintuitive to assume that firms would stay on the demand curve when markup is negative.[3] Conversely, markup responses are smoother in the benchmark model because financially constrained firms raise pass-through to maintain profitability. As a result, the benchmark model avoids the problem of negative markups and is also closer to my empirical findings in terms of profit margins. Second, the nonlinear Phillips curve exerts destabilizing effects on the macroeconomy. Consistent with the intuition of Bhattarai et al. (2018), lower price rigidities lower welfare by amplifying both inflation and the output loss. Worse, the destabilizing effects are particularly strong during large negative shocks, given the nonlinearity of the price rigidity channel.

Lastly, inflation can feed back to borrowing constraints depending on how monetary policy reacts to inflation. When profits are procyclical, aggressive monetary policy depresses demand and lowers profits, pushing financially constrained firms further to flexible prices. By contrast, while accommodative monetary policy can relax financial constraints and restore price rigidities, it is also inflationary by itself. As such, the price rigidity channel poses difficult monetary policy trade-offs, particularly during large shocks.

Literature. This paper contributes to several strands of the macro literature. The most related is the vast literature on the finance-price nexus. Most papers focus on prices (e.g., Chevalier and Scharfstein, 1996, Gilchrist et al., 2017, Kim, 2021, Lenzu et al., 2024, Balduzzi et al., 2024, Renkin and Züllig, 2024), while few others examine markups (Montero and Urtasun, 2021) and the frequency of price changes (Balleer et al., 2017, Berardi, 2025). Compared to previous work, this paper makes both empirical and theoretical contributions. Empirically, I go beyond the previous focus on prices by estimating the effects on cost pass-through, thanks to the granular data on input prices, output prices, and balance sheets that are not often available for large samples. The closest paper to my knowledge is Strasser (2013), who looks at how financial constraints affect exchange rate pass-through. My paper complements Strasser (2013) by examining domestic prices set by primarily non-exporters and analyzing the macroeconomic implications. Theoretically, I show that the interplay between financial constraints and price rigidities, on top of prices, yields important nonlinearity in the New Keynesian framework. Such interactions and nonlinearity are not yet studied in previous macro papers such as Gilchrist et al. (2017). Qualitatively, both Gilchrist et al. (2017) and my model would predict amplified inflation when large shocks squeeze the profitability of financially constrained firms. However, the mechanisms are distinct. My price rigidity channel originates from a minimalist model that does not require customer bases, whereas credit shocks do not steepen the Phillips curve in Gilchrist et al. (2017). In a slightly different setting, Christiano et al. (2015) study how financial shocks raise marginal costs and thus prices through the working capital channel. Conversely, Kim (2021) shows that financially constrained firms may sell off inventories to raise cash flows,

[3] More broadly, Holden (2024) points out that the problem of negative markups can occur in a simple trend inflation model with Calvo pricing even without large shocks.

leading to depressed output prices. These channels, though out of this paper's scope, are not mutually exclusive from my price rigidity channel because the latter does not rely on any particular assumption about customer bases, inventories, or working capital.

The paper also contributes to the growing literature on the nonlinearity of the Phillips curve. Several papers, especially after the Covid inflation, emphasize the role of the labor market in the nonlinearity of the output-based Phillips curve (e.g., Forbes et al., 2022, Ball et al., 2022, Benigno and Eggertsson, 2023, Schmitt-Grohé and Uribe, 2022). A different approach is to generate nonlinearity in the marginal cost-based Phillips curve through menu costs (Blanco et al., 2024, Gagliardone et al., 2024) or the shape of the demand curve (Harding et al., 2023). My model differs from these papers by generating nonlinearity through occasionally binding financial constraints.

Third, by incorporating the financial dimension, the paper contributes to the nascent literature on estimating pricing functions using granular product-level data (Amiti et al., 2019, Gagliardone et al. (2023), Alexander et al., 2024). Amiti et al. (2019) identify direct cost pass-through of 0.6 and strategic complementarities of 0.4 using micro data and emphasize the importance of size heterogeneity. Remarkably, my estimates for financially unconstrained firms are largely in line with Amiti et al. (2019), albeit using a different sample in a very different country. Gagliardone et al. (2023) apply the Amiti et al. (2019) approach to a dynamic setting with Calvo pricing frictions. With high-quality quarterly data, they jointly estimate pricing frictions and strategic complementarities, two key parameters shaping the marginal cost-based Phillips curve. While I do not have high-frequency data in Prowess to estimate structural parameters as in Gagliardone et al. (2023), the availability of balance sheet data allows me to study financial constraints that are unavailable in the previous two studies.

Finally, this paper complements the investment channel in New Keynesian models with financial heterogeneity (e.g., Khan and Thomas, 2013, Ottonello and Winberry, 2020, Caglio et al., 2021). For computational reasons, rich models with financial heterogeneity and investment such as Ottonello and Winberry (2020) often add nominal rigidities only to the retailer sector that faces no financial constraints, therefore mechanically separating finance and pricing. If financially constrained firms can adjust along both pricing and investment margins, the interactions of the two can be useful for future research.

The rest of the paper is organized as follows. In Section 2 I illustrate the price rigidity channel in a minimalist model. In Section 3 I present the empirical evidence. In Section 4 I study the price rigidity channel in a New Keynesian model.

2 Intuitions behind the Price Rigidity Channel

In this section, I provide a minimalist model of the intermediate goods sector to show how nominal rigidities interact with financial constraints.

2.1 Model Setup

Production. Each intermediate goods firm i has the following production function, consisting of labor $L_{i,t}$, productivity $A_{i,t}$, and fixed production costs ω.[4]

$$Y_{i,t} = A_{i,t} L_{i,t}^{1-\gamma} - \omega. \tag{2.1}$$

I assume that $A_{i,t}$ is the product of (i) aggregate productivity A_t and (ii) an idiosyncratic component $\tilde{A}_{i,t}$, i.e., $A_{i,t} = A_t \tilde{A}_{i,t}$. $\ln \tilde{A}_{i,t}$ follows an AR(1) process.

$$\tilde{a}_{i,t} = \rho_a \tilde{a}_{i,t-1} + \varepsilon^a_{i,t}, \quad \text{where} \quad \tilde{a}_{i,t} = \ln \tilde{A}_{i,t} \text{ and } \varepsilon^a_{i,t} \sim N(0, \sigma_a^2). \tag{2.2}$$

EBITDA ($\text{EBITDA}_{i,t}$) equals revenues minus production costs. Let W_t be the nominal wage paid by firms.

$$\text{EBITDA}_{i,t} = P_{i,t} Y_{i,t} - W_t L_{i,t}. \tag{2.3}$$

Nominal rigidities. Firms are subject to a price adjustment cost $\mathscr{C}_{i,t}$ à la Rotemberg (1982). The degree of nominal rigidities is governed by τ_p as defined in equation 2.4. P_t and Y_t are aggregate price and output, respectively. Importantly, $\mathscr{C}_{i,t}$ is a non-monetary cost, i.e., it is not considered an accounting expense. In Section 5, I show that my main results do not change when I use Calvo or menu-cost models.

$$\mathscr{C}_{i,t} = \frac{\tau_p}{2} \pi_{i,t}^2 P_t Y_t, \quad \text{where } \pi_{i,t} = \ln \frac{P_{i,t}}{P_{i,t-1}}. \tag{2.4}$$

Financial frictions. Debt financing is frictional in this model. At time t, firm i issues one-period debt $D_{i,t}$ subject to an earnings-based borrowing constraint specified in equation 2.5, where ϕ is the maximum debt-to-EBITDA ratio.

$$D_{i,t} \leq \phi \max(\text{EBITDA}_{i,t},\ 0). \tag{2.5}$$

Interest expenses at $t+1$ ($\text{Interest}_{i,t+1}$) equal $D_{i,t}$ multiplied by the nominal borrowing rate $r^b_{i,t+1}$. $r^b_{i,t+1}$ is taken as given and known at t, while the realized real borrowing rate $r^{b,r}_{i,t+1}$ depends on the realized inflation at $t+1$. There is no default for simplicity. Finally, why do firms borrow in this setting? In the absence of capital and investment, I assume that firms borrow for the sole purpose of smoothing cash flows during adverse shocks.

Apart from financing limits, I also assume costly equity issuance. Given that raising equity is equivalent to paying out negative dividends (defined below in equation 2.8) in this model, having costly equity issuance is the same as having a penalty when dividends fall below zero. In other words, the equity financing friction can also be interpreted as a liquidity constraint. In equation 2.6, I assume a non-monetary penalty term that is linear in dividends when dividends

[4] Note that equation 2.1 has no capital for simplicity. It is a reasonable simplification so long as the investment adjustment costs are larger than price adjustment costs, in which case firms will adjust prices first and then capital expenditure.

are negative:

$$\mathscr{E}_{i,t} = -\tau_e \min(0, \mathrm{Div}_{i,t}). \tag{2.6}$$

Importantly, τ_e captures not only the financial cost of equity issuance but also the opportunity cost of not being able to obtain equity promptly. For a firm that has no access to capital markets, τ_e is effectively infinite. Similarly, if a firm can issue equity at a low cost but issuance takes a prolonged period, one should still assume a high τ_e to account for the unavailability of equity in the short run.[5] Note that equation 2.6 is similar to the per-unit dilution cost for equity issuance assumed in Gilchrist et al. (2017). Nonetheless, unlike in Gilchrist et al. (2017) where the dilution cost is externally calibrated, I will be able to set τ_e such that the model matches pricing behaviors in the empirical analysis in Section 3.

Nominal profits and dividends. Profits are defined as EBITDA minus interest payments. $\mathscr{C}_{i,t}$ and $\mathscr{E}_{i,t}$ are not accounting costs and thus not included.

$$\mathrm{Profit}_{i,t} = \mathrm{EBITDA}_{i,t} - \mathrm{Interest}_{i,t}. \tag{2.7}$$

Dividends are defined as profits plus changes in net borrowing. For instance, firms can save by restricting dividends to lower $D_{i,t}$. Negative $D_{i,t}$ means having a positive cash buffer.

$$\mathrm{Div}_{i,t} = \mathrm{Profit}_{i,t} + (D_{i,t} - D_{i,t-1}). \tag{2.8}$$

Objective. Let $\Lambda_{t,t+h}$ be the stochastic discount factor from t to $t+h$. Each firm i chooses $\{P_{i,t}, D_{i,t}\}$ to maximize real dividends minus non-monetary costs:

$$\max_{\{P_{i,t}, D_{i,t}\}} \mathrm{E}_t \sum_{h=0}^{\infty} \Lambda_{t,t+h} \frac{1}{P_{t+h}} \left[\mathrm{Div}_{i,t+h} - (\mathscr{C}_{i,t+h} + \mathscr{L}_{i,t+h} + \mathscr{E}_{i,t+h})\right], \tag{2.9}$$

subject to

$$\begin{aligned} \text{Nominal rigidities:} \quad & \mathscr{C}_{i,t} = \frac{\tau_p}{2} \pi_{i,t}^2 P_t Y_t; && (2.10)\\ \text{Borrowing constraint:} \quad & \phi \max(\mathrm{EBITDA}_{i,t},\ 0) - D_{i,t} \geq 0; && (2.11)\\ \text{Equity/liquidity constraint:} \quad & \mathscr{E}_{i,t} = -\tau_e \min(0, \mathrm{Div}_{i,t}). && (2.12) \end{aligned}$$

2.2 Optimal Prices

Demand elasticity. On the demand side, $Y_{i,t}$ is a differentiable function of (i) firm i's current price $P_{i,t}$ and (ii) variables exogenous to firm i, such as aggregate variables and competitors'

[5]There are several ways to account for the time dimension more explicitly, though differences are small for our purposes. For example, one can explicitly model the issuance delay by assuming a cost schedule that is decreasing in the time it takes to issue equity. For unanticipated business cycle shocks, the difference is trivial. Alternatively, one can set up the penalty term as a fixed cost plus a linear component. The advantage is that the slope of the linear component is the observed cost of equity conditional on issuance, which is observed in the data. In reality, equity issuance is often procyclical, suggesting that most firms are in the inaction regime.

prices.[6] By including competitors' prices, it nests the class of models with oligopolistic competition (e.g., Amiti et al., 2019, Wang and Werning, 2022). Define firm i's demand elasticity $\epsilon_{i,t}$:

$$\epsilon_{i,t} = -\frac{\partial y_{i,t}}{\partial p_{i,t}}, \quad \text{where } y_{i,t} = \ln Y_{i,t} \text{ and } p_{i,t} = \ln P_{i,t}. \tag{2.13}$$

Optimality conditions. The full derivation is in Appendix B. The first-order condition (FOC) with respect to $P_{i,t}$ is given by:

$$\pi_{i,t} = \big(\underbrace{1 + \xi^{div}_{i,t} + \xi^{ebc}_{i,t}\phi_i}_{\xi_{i,t}}\big)\frac{\epsilon_{i,t}-1}{\tau_p}\frac{P_{i,t}Y_{i,t}}{P_tY_t}\Big[\mathscr{M}_{i,t}MC_{i,t}\frac{P_t}{P_{i,t}} - 1\Big] + \mathrm{E}_t\,\Lambda_{t,t+1}\frac{Y_{t+1}}{Y_t}\pi_{i,t+1}, \tag{2.14}$$

where (i) $\mathscr{M}_{i,t} = \frac{\epsilon_{i,t}}{\epsilon_{i,t}-1}$, (ii) $MC_{i,t} = \frac{\partial L_{i,t}}{\partial Y_{i,t}}\frac{W_t}{P_t} = \frac{W_t}{P_t}\frac{1}{1-\gamma}\Big(\frac{Y_{i,t}+\omega_i}{A_{i,t}}\Big)^{\frac{\gamma}{1-\gamma}}$ (real marginal cost), and (iii) $\xi^{div}_{i,t}$ and $\xi^{ebc}_{i,t}$ are the Lagrangian multipliers on the equity financing friction and the borrowing constraint, respectively.[7]

The two Lagrangian multipliers, $\xi^{div}_{i,t}$ and $\xi^{ebc}_{i,t}$, evolve according to the borrowing FOCs:

$$\xi^{ebc}_{i,t} = (1 + \xi^{div}_{i,t}) - \mathrm{E}_t\,\Lambda_{t,t+1}(1 + r^{b,r}_{i,t+1})(1 + \xi^{div}_{i,t+1}), \quad \text{where} \quad \xi^{div}_{i,t} \le \tau_e. \tag{2.15}$$

Recall that $r^{b,r}_{i,t+1}$ is the real borrowing cost and $\Lambda_{t,t+1}$ is the one-period-ahead discount factor. Meanwhile, financial constraints can be no tighter than $\xi^{div}_{i,t} = \tau_e$ because otherwise firms will resort to equity financing.

2.3 Endogenous Nominal Rigidities

Let $\xi_{i,t} = \xi^{div}_{i,t} + \xi^{ebc}_{i,t}\phi_i$, which summarizes the overall tightness of financial constraints. From equation 2.14, it is straightforward that $\xi_{i,t}$ directly increases the slope of the marginal cost term in the pricing FOC. What does it mean to price rigidities? To answer it, it would be useful to examine the limiting case where (i) $\xi_{i,t} \to \infty$ and (ii) $\forall h, \frac{\xi_{i,t}}{\xi_{i,t+h}} \to \infty$. Economically, the limiting case means that firm i faces an acute need for short-term cash flows.[8]

Let $P^*_{i,t}$ be the optimal *sticky* price, which is the fixed point solution to equation 2.14. In

[6] One can further generalize the demand function by including past $P_{i,t}$, and then the demand function nests the class of models with habits or customer markets (e.g., Ravn et al., 2006, Gilchrist et al., 2017). Nonetheless, this does not change propositions 1 and 2 below because all past and future $P_{i,t}$'s drop out in the limiting case. As such, I do not include past $P_{i,t}$ to keep the derivation concise.

[7] For simplicity, I assume that EBITDA is always positive when deriving equation 2.14. I relax the assumption when numerically solving the model in Section 4, and the intuition remains the same.

[8] Since $\xi^{div}_{i,t} \le \tau_e$, in this limiting case we also need $\tau_e \to \infty$, i.e., equity financing is forbidden in the limiting case. The second condition, $\frac{\xi_{i,t}}{\xi_{i,t+h}} \to \infty$, means that financial needs are only acute today and will fade away in the future. Since the paper focuses on the business cycle frequency, firms facing high but permanent financial constraints, perhaps due to the lack of financial development or other structural factors, are beyond the scope of the paper.

the limiting case where (i) $\xi_{i,t} \to \infty$ and (ii) $\forall h, \frac{\xi_{i,t}}{\xi_{i,t+h}} \to \infty$, equation 2.14 converges to equation 2.16, which is also the optimality condition under *flexible* prices.

$$P_{i,t} = \mathscr{M}_{i,t} MC_{i,t} P_t. \tag{2.16}$$

In other words, the optimal sticky price converges to the optimal flexible price in the limiting case. Denote the optimal flexible price as $P^f_{i,t}$ and summarize the finding in Proposition 1:

Proposition 1 (Nominal Rigidities and Financial Constraints) *In the limiting case where (i) $\xi_{i,t} \to \infty$ and (ii) $\forall h, \frac{\xi_{i,t}}{\xi_{i,t+h}} \to \infty$, the optimal sticky price $P^*_{i,t}$ converges to the optimal flexible price $P^f_{i,t}$ as in equation 2.17. Hence, tight financial constraints weaken nominal rigidities.*

$$\lim_{\xi_{i,t} \to \infty} P^*_{i,t} = P^f_{i,t}, \quad \text{where } P^f_{i,t} \text{ satisfies } P_{i,t} = \mathscr{M}_{i,t} MC_{i,t} P_t\ . \tag{2.17}$$

What is the economic intuition behind proposition 1? A sticky-price firm in urgent need of short-term cash flows sets prices like a flexible-price firm to maximize current EBITDA and ignores future costs resulting from nominal rigidities.

From proposition 1, one can easily have corollary 1 regarding direct cost pass-through under constant returns to scale (CRS) and constant elasticity of substitution (CES) .

Corollary 1 (Complete Cost Pass-through) *Under CRS and CES, direct cost pass-through is complete in the limiting case where $\xi_{i,t} \to \infty$ and $\forall h, \frac{\xi_{i,t}}{\xi_{i,t+h}} \to \infty$.*

2.4 Endogenous Strategic Complementarities

Besides nominal rigidities, equation 2.14 is also suitable for analyzing one particular type of real rigidities, namely the strategic complementarities in price setting. If one substitutes the expectation term through iterating equation 2.14 forward, one can find $\epsilon_{i,t+h}$ in equation 2.14 for all $h \geq 0$. Thus, strategic complementarities can arise in equation 2.14 so long as for some competitors j, their prices $P_{j,t}$ have a positive impact on firm i's demand elasticity $\epsilon_{i,t+h}$ for some $h \geq 0$. Similar to Amiti et al. (2019), I focus on cases where $P_{j,t}$ can be aggregated in the sense that there exists an index of competitor price changes $dp_{-i,t}$ such that for all $h \geq 0$, $\frac{\partial \epsilon_{i,t+h}}{\partial p_{-i,t}}$ is well-defined and is a sufficient statistic for $\frac{\partial \epsilon_{i,t+h}}{\partial p_{j,t}}$. Mathematically, it means that

$$\frac{\partial \epsilon_{i,t+h}}{\partial p_{-i,t}} dp_{-i,t} = \sum_{j \neq i} \frac{\partial \epsilon_{i,t+h}}{\partial p_{j,t}} dp_{j,t}. \tag{2.18}$$

Observe that only $\epsilon_{i,t}$ remains in the limiting case of equation 2.16. Therefore, whether $P_{-i,t}$ changes $\epsilon_{i,t}$ makes a key difference. If it does, the effect will be even stronger in the limiting case through the $\mathscr{M}_{i,t}$ term. If it does not, there will be no room for strategic complementarities in the limiting case. The two cases are summarized in proposition 2.

Proposition 2 (Strategic Complementarities and Financial Constraints) *Holding marginal costs constant, in the limiting case where (i)* $\xi_{i,t} \to \infty$ *and (ii)* $\forall h, \frac{\xi_{i,t}}{\xi_{i,t+h}} \to \infty$

- *If* $\frac{\partial \epsilon_{i,t}}{\partial p_{-i,t}} > 0$, *strategic complementarities strengthen in the limiting case, i.e., tight financial constraints amplify strategic complementarities.*
- *If (i)* $\frac{\partial \epsilon_{i,t}}{\partial p_{-i,t}} = 0$ *and (ii)* $\frac{\partial \epsilon_{i,t+h}}{\partial p_{-i,t}} > 0$ *for some* $h \geq 1$, *strategic complementarities vanish in the limiting case, i.e., tight financial constraints weaken strategic complementarities.*

How to make sense of the second part of proposition 2? Imagine an economy with product market frictions such that it takes time for customers to search for new sellers. If competitors change their prices at t, customers will not switch away until $t+1$, and firm i's demand will not be affected until then. In the limiting case, firm i would like to raise as much internal cash flows as possible no matter how many customers will switch away in the future.

3 Empirical Evidence on the Price Rigidity Channel

Propositions 1 and 2 provide key insights regarding how financial constraints change pricing decisions. In this section, I empirically test the channel using the method built on Amiti et al. (2019) (AIK hereafter).[9]

3.1 Data

The main data source is the Prowess database maintained by the Centre for Monitoring the Indian Economy (CMIE) for the period between March 1992 and March 2011, a period during which India experienced large variations in price levels (see Figure A1).[10] Details of the Prowess database are discussed extensively in Goldberg et al. (2010a), Goldberg et al. (2010b), De Loecker et al. (2016). The most unique feature of this database is that it includes both financial statements *and* product-level price data for a large annual panel of Indian firms. This is indispensable to studying the price rigidity channel hypothesized in this paper. The granular data on prices and quantities of intermediate inputs also allow me to extend the identification strategy in AIK in Section 3.2.1.

Below I explain the main steps to construct the variables. Detailed procedures to clean and construct the data panel are documented in Section D.1. In terms of notation, products are indexed by p. Consistent with Section 2, firms, time, and 2-digit sectors are indexed by i, t, and s, respectively. In cases where I use s to denote 4-digit industries, I explicitly address it in the text.

[9] An alternative method is the rational-expectation GMM in Gagliardone et al. (2023) (GGLT hereafter). Compared to GGLT's method, AIK's method is more versatile and easier to extend. Additionally, the rational expectation assumption appears too restrictive for my sample period, where forecasters constantly underestimated inflation in India since 2006 (e.g., see IMF WEO forecast vintages).

[10] The legal requirement for data reporting changed after 2011, and product-level price data became less available thereafter.

3.1.1 Products

Output products. While the model in Section 2 is not explicitly a multi-product/industry model, I follow AIK to aggregate product prices to the firm level and control for firm scope in the regressions.

Prowess provides product names and proprietary product classification codes that are highly consistent over time, even though it does not have unique product identifiers. Thus, I identify a unique product by requiring exactly the same product name, the same classification code, and the same producer.[11] In addition, I determine whether products belong to the same 2-digit sectors, 4-digit industries, or 6-digit narrow industries based on product codes. The industry classification of a firm is based on the product code of its main products.

Manufacturing products are in the following 2-digit sectors: $[27,57]$ and $[63,70]$. For a firm to be a manufacturing firm in a given year, (i) it needs to have over 70% of sales from manufacturing products in that year, and (ii) the industry where it operates (based on its main product) should be in the manufacturing sector.

Intermediate goods. Prowess also collects data on intermediate inputs, including prices, quantities, product codes, and names. Prowess uses the same classification system for intermediate goods and output products. I identify a unique intermediate input by requiring exactly the same product name, the same classification code, and the same buyer.

Major intermediate goods. I define major intermediate goods as intermediate goods from major 6-digit industries, and major industries are the top 10% industries ranked by the number of unique buyers in the sample period in Prowess. Major 6-digit industries have 152 or more unique buyers that are included in the Prowess sample.

3.1.2 Price Variables

Output price changes. First, I calculate log price changes, $\Delta p_{i,p,t}$, at the product level for manufacturing products. Following AIK, I drop observations with extreme log changes above $\ln(3)$ or below $-\ln(3)$.[12]

Most firms have more than one manufacturing product. I compute firm-level price changes from $t-1$ to t, $\Delta p_{i,t}$, using the standard Törnqvist index that averages product-level price changes weighted by average sales between $t-1$ and t. Denote the weight (within all products with non-missing $\Delta p_{i,p,t}$) as $s^{\text{sales}}_{i,p,t}$:

$$\Delta p_{i,t} = \sum_p s^{\text{sales}}_{i,p,t} \Delta p_{i,p,t}, \quad \sum_p s^{\text{sales}}_{i,p,t} = 1. \tag{3.1}$$

[11] The drawback of this method is that if the same product is reported under different names over time, it will create more missing observations than what is truly missing.

[12] Many extreme price changes come from misplacing the decimal point (e.g., 3.11 is written as 31.1 or 311). I correct these errors (explained in Section D.1) before dropping observations.

Similarly, one can define firm-level output changes as below:

$$\Delta y_{i,t} = \sum_p s^{\text{sales}}_{i,p,t} \Delta y_{i,p,t}. \tag{3.2}$$

To reduce measurement errors, I calculate firm-level price and output changes only when the Törnqvist index covers over 50% of manufacturing product sales in a given year for a given firm.

Intermediate price changes. Define $\rho_{i,t}$ as the logged unit price for total material inputs and $x^{\text{input}}_{i,t}$ as the expenditure share of materials in the cost of goods sold (COGS). As in AIK, I assume that changes in $\rho_{i,t}$ equal the average changes in all individual inputs weighted by average expenditure share between $t-1$ and t.

Let $\Delta\rho^{\text{mj}}_{i,t}$ be the average price change of major intermediate goods and $\Delta\rho^{\text{other}}_{i,t}$ be the average price change of other intermediate goods, both weighted by average purchases. Their expenditure shares are $x^{\text{mj}}_{i,t}$ and $x^{\text{other}}_{i,t}$, respectively. Changes in $\rho_{i,t}$ are decomposed as follows:

$$x^{\text{input}}_{i,t} \Delta\rho_{i,t} = x^{\text{mj}}_{i,t} \Delta\rho^{\text{mj}}_{i,t} + x^{\text{other}}_{i,t} \Delta\rho^{\text{other}}_{i,t}, \quad x^{\text{mj}}_{i,t} + x^{\text{other}}_{i,t} = x^{\text{input}}_{i,t}, \tag{3.3}$$

To simplify notation, I use $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t}$ instead of $x^{\text{mj}}_{i,t}\Delta\rho^{\text{mj}}_{i,t}$ hereafter.

Average output price changes of competitors. I compute average price changes of i's competitors, $\Delta p_{-i,t}$, in two steps. First, for each product p, I construct average competitor price changes $\Delta p_{-i,p,t}$ weighted by average sales from $t-1$ to t. Competitors are firms who sell products within the same 6-digit industries, and I only calculate $\Delta p_{-i,p,t}$ when there are at least 5 competitors with non-missing data in 6-digit industries (~10th percentile). Denote the average market share of firm j's product p from $t-1$ to t as $s^{\text{mkt}}_{j,p,t}$.

$$\Delta p_{-i,p,t} = \sum_j \frac{s^{\text{mkt}}_{j,p,t}}{1 - s^{\text{mkt}}_{i,p,t}} \Delta p_{j,p,t}, \quad \sum_j s^{\text{mkt}}_{j,p,t} = 1 - s^{\text{mkt}}_{i,p,t}. \tag{3.4}$$

Second, for each firm i, its competitor price change $\Delta p_{-i,t}$ is the average of all its $\Delta p_{-i,p,t}$ weighted by i's average sales of p. Denote the weight as $\widetilde{s^{\text{sales}}_{i,p,t}}$.[13] Again, I calculate $\Delta p_{-i,t}$ only when it covers over 50% of manufacturing sales.

$$\Delta p_{-i,t} = \sum_p \widetilde{s^{\text{sales}}_{i,p,t}} \Delta p_{-i,p,t}, \quad \sum_p \widetilde{s^{\text{sales}}_{i,p,t}} = 1. \tag{3.5}$$

Average intermediate price changes of competitors. Each competitor j has its own $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{j,t}$ and $\Delta\rho^{\text{mj}}_{j,t}$, and I aggregate up the two terms using equations 3.4 and 3.5. For each $z_{j,t} \in \{(x^{\text{mj}}\Delta\rho^{\text{mj}})_{j,t},$

[13] Note that $\widetilde{s^{\text{sales}}_{i,p,t}}$ (which is within all products with non-missing $\Delta p_{-i,p,t}$) is proportional to but not the same as $s^{\text{sales}}_{i,p,t}$ in equation 3.1 (which does not require non-missing $\Delta p_{-i,p,t}$).

$\Delta\rho^{\text{mj}}_{j,t}\}$, we define:

$$z_{-i,p,t} = \sum_{j\in Z} \frac{s^{\text{mkt}}_{j,p,t}}{1 - s^{\text{mkt}}_{i,p,t}} z_{j,t}, \quad \text{and} \quad z_{-i,t} = \sum_{p} \widetilde{s^{\text{sales}}_{i,p,t}} z_{-i,p,t}. \tag{3.6}$$

Denote the two resulting cost measures as $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{-i,t}$ and $\Delta\rho^{\text{mj}}_{-i,t}$.

3.1.3 Marginal Costs

As in AIK, I use log changes in average variable costs, i.e., total variable costs divided by output quantity, as a proxy for log changes in nominal marginal costs.

$$\Delta mc^{\text{nom.}}_{i,t} = \Delta \ln \frac{\text{TVC}_{i,t}}{Y_{i,t}}. \tag{3.7}$$

Real output $Y_{i,t}$ is obtained by deflating nominal sales of manufacturing products by the firm-level price we derived above. The total variable cost variable $\text{TVC}_{i,t}$ is measured by the cost of goods sold (COGS) on the income statement. In the case where sales consist of non-manufacturing sales, I allocate COGS proportionally, i.e., $\text{TVC}_{i,t} = \text{COGS}_{i,t} \times \text{Mfg. Sales}_{i,t} \,/\, \text{Sales}_{i,t}$.

3.1.4 Financial Variables

As mentioned in the introduction, three commonly used ratios are used to gauge the tightness of the financial constraints.

The EBITDA-to-sales ratio. The first one is the EBITDA-to-sales ratio, defined as a firm's EBITDA over total income in Prowess. The main advantage of using the EBITDA ratio is that it is directly informed by the model. After all, EBITDA (or its shadow value) is what drives the price rigidity channel in equation 2.14. When EBITDA is low, firms face greater liquidity and/or solvency risks when negative shocks hit.

Different sectors may have very different secular trends in their profitability, which prevents me from pooling different sectors meaningfully in the regression. In Panel (a) of Figure A2, I plot the density function of the EBITDA ratio for all firms in each sector-year used in the regression sample. Each thin gray line is the density curve for all firms in the same sector-year. The black line is the density curve for all firms in all sector-years. Not surprisingly, the density curves show considerable heterogeneity. Note that part of the heterogeneity reflects the fact that the whole sector is hit by cyclical shocks in a given year, while heterogeneity can also arise from changes in technology or business models that are unrelated to financial constraints. Not being able to distinguish the two, I exclude both by removing the 2-digit sector-year median from the EBITDA ratio. In Panel (d) of Figure A2, I plot the density functions of the re-centered EBITDA ratio. The re-centered density curves are much more comparable with each other, suggesting that the re-centered EBITDA ratio is more suitable for my empirical analysis.[14]

[14] The only exception is the "Fats & oils and derived products" sector, which has noticeably high kurtosis in panel (d); however, the sector only accounts for less than 3% of the regression sample.

Finally, I convert the re-centered EBITDA ratio into a binary dummy for simplicity. A firm is classified as a low-EBITDA firm at t if its re-centered EBITDA ratio at $t-2$ is below the 25th percentile in the regression sample. Low-EBITDA firms are economically important: they account for around 18% of sales in the regression sample. The low-EBITDA dummy has relatively high within-firm variation. 65% of firms are considered low-EBITDA for at least once. Only 19% of firms are considered low-EBITDA for over 50% of the time, and 7.5% for over 80% of the time. Only 2.7% of firms always have low EBITDA. Finally, for robustness, I relax the binary assumption in Section 3.3.4.

The ICR and the DSCR. Besides the EBITDA ratio, I also use the interest coverage ratio (ICR) and the debt service coverage ratio (DSCR), both calculated by Prowess. In particular, the DSCR is defined as cash profits divided by the current portion of a firm's debt obligations, whereas cash profits are defined as after-tax profits adjusted for non-cash and extraordinary items. Compared to measures such as leverage and the debt-to-EBITDA ratio, the DSCR is more comparable across firms because the denominator has the same maturity (i.e., one year) for all firms. By contrast, the leverage ratio conceal potentially huge heterogeneity in maturity structures.[15]

Compared to the EBITDA ratio, the ICR and the DSCR have even greater sectoral heterogeneity that impedes direct comparison across firms. In panels (b) and (c), I plot the density function of the ICR and the DSCR, respectively, for all firms in each sector-year. Noticeably, Heterogeneity is particularly high in the left tail in both panels. Given the high heterogeneity, I remove the 6-digit sector-year median from both ratios. The resulting density functions are plotted in panels (e) and (f) of Figure A2. The re-centered density curves are more comparable, though they still show more heterogeneity compared to the re-centered EBITDA ratio. In this sense, the EBITDA ratio is preferred over the ICR and the DSCR for its cross-sector comparability.

Finally, I convert the ICR and the DSCR into binary dummies as above. The threshold is the 25th percentile in the regression sample. Low-ICR (low-DSCR) firms account for 18% (20%) of sales. Both the ICR and the DSCR have slightly higher within-firm variation than EBITDA. 73% (71%) are considered low-ICR (low-DSCR) for at least once. Only 14% (14%) of firms are considered low-ICR (low-DSCR) for over 50% of the time, and 3.6% (4.6%) of firms for over 80% of the time. Merely 0.5% (1.3%) of firms are always low-ICR (low-DSCR).

3.1.5 Other Variables

A firm's market share is defined as the average market share of each product in its 6-digit industry weighted by sales at t. Industry scope is the number of unique 6-digit manufacturing industries where a firm has positive sales in a given year. A firm's exporter status is determined by the share of its export revenues in its total income, as reported directly by Prowess. To determine a firm's relative size at t, I calculate the average log asset size from $t-1$ to t relative to the manufacturing sample average in the same period.

[15] Unfortunately, Prowess does not have maturity information for my sample period, so it is impossible to use the identification strategy in Almeida (2012).

	High EBITDA ($N = 7,331$)				Low EBITDA ($N = 2,407$)			
	P10	Median	P90	S.D.	P10	Median	P90	S.D.
A. Firm Size (in constant 1990 Rupees)								
Sales (in log)	4.19	5.74	7.09	1.11	3.89	5.34	6.80	1.10
Assets (in log)	4.15	5.64	7.11	1.11	3.65	4.87	6.53	1.07
B. Profit Margins and Financial Ratios								
COGS margin	14.5	27.3	41.8	10.8	8.7	21.7	37.1	11.1
EBITDA margin	5.0	12.4	22.1	7.4	-0.1	5.9	13.2	6.9
Current liability-to-asset ratio	6.4	16.5	35	12.7	10.0	25.9	52.7	18.5
Leverage ratio	13.6	38.6	62.8	19.7	13.9	37.6	90.9	26
Interest coverage ratio (ICR)	0.2	2.0	9.8	12.9	0.0	1.3	5.3	8.7
Debt service coverage ratio (DSCR)	0.6	2.7	10.4	12.6	-0.2	1.8	6.3	9.7
Current ratio	0.8	1.2	2.0	0.6	0.6	1.2	1.9	0.6
C. Price Changes								
$\Delta p_{i,t}$	-11.0	3.0	19.6	14.2	-10.8	3.7	21.8	15.4
$\Delta mc^{\text{nom.}}_{i,t}$	-11.7	4.1	22.0	15.1	-12.9	3.9	23.0	16.2
$\Delta p_{-i,t}$	-4.9	2.7	13.3	8.4	-5.0	2.7	14.1	8.7
$(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t}$	-6.7	1.8	13.7	9.5	-7.7	1.6	14.3	10.2
$(x^{\text{mj}}\Delta\rho^{\text{mj}})_{-i,t}$	-2.8	1.9	8.6	5.3	-3.5	1.9	9.7	6.1
D. Other Characteristics								
Share of imported raw materials	0.0	0.6	43.9	20.9	0.0	0.0	31.1	17.9
Share of export revenues	0.0	3.6	38.5	17.8	0.0	0.3	23.4	13.1
Industry scope	1.0	1.0	3.0	0.83	1.0	1.0	3.0	0.75
Market share	0.1	0.6	4.1	2.9	0.1	0.4	3.7	2.6

Notes: The table summarizes the regression sample in column (1) of Table 2. Sales and assets are deflated by the Wholesale Price Index (WPI), and I normalize the WPI such that its 1990 value equals 100. The COGS margin is defined as (total income - COGS) divided by total income. The current ratio, calculated by Prowess, is defined as current assets divided by current liabilities. The share of imported raw materials is the value of imported raw materials as a percentage of all materials consumed. Market share and industry scope are based on 6-digit industries, as defined in Section 3.1.5. The COGS margin, EBITDA margin, current liability-to-asset ratio, leverage ratio, and all variables in panel D are in percentage points. The ICR, DSCR, and the current ratio are *not* multiplied by 100. All variables in panel C are log changes multiplied by 100.

Table 1: Summary Statistics

3.1.6 Summary Statistics

In Table 1, I report separately the characteristics of high-EBITDA and low-EBITDA observations in my regression sample. The regression sample corresponds to my main regression in column (1) of Table 2. Sample restrictions are detailed in Section 3.2.1.

As expected, low-EBITDA firms have lower profit margins and worse financial rations compared to high-EBITDA ones as shown in panel (b). The only exception is the leverage ratio: low-EBITDA and high-EBITDA firms have similar median leverage ratios, yet low-EBITDA firms are more likely to have extremely high leverage (see the 90th percentile). This observation confirms my previous conjuncture that the leverage ratio in this dataset cannot fully reveal the heterogeneity in financial health and is therefore inferior to other measures.

Second, as shown in panel (a), low-EBITDA firms are systematically smaller. This is not surprising given that financial constraints are often correlated with size (e.g., Hadlock and Pierce, 2010). Nonetheless, in theory, size can also affect pass-through and strategic complementarities for non-financial reasons. For instance, Amiti et al. (2019) already show that small firms can have higher pass-through but lower strategic complementarities because their demand elasticity is less sensitive to changes in their market share. This observation motivates my robustness check in Section 3.5, in which I show that my results remain valid after controlling for the size factor.

Third, high- and low-EBITDA firms are similar in terms of price-related variables, imports, industry scope, and market share. High-EBITDA firms have slightly more exports than low-EBITDA firms, though the revenue share is very low for both types. The similarity partly results from the sample restrictions I impose.

Finally, I split the sample by the ICR dummy and the DSCR dummy and report the summary statistics in Tables A1 and A2, respectively. The patterns are largely similar.

3.2 Specifications and Identification

3.2.1 Baseline Specification

The baseline specification in equation 3.8 features double interactions with a pre-determined financial constraint dummy to test how financial constraints affect pricing.

$$\begin{aligned}\Delta p_{i,t} = &\underbrace{\beta_0 \Delta mc_{i,t} + \beta_1 \mathbb{1}^{\text{Tight}}_{i,t} \Delta mc_{i,t}}_{\text{Direct cost pass-through}} + \underbrace{\gamma_0 \Delta p_{-i,t} + \gamma_1 \mathbb{1}^{\text{Tight}}_{i,t} \Delta p_{-i,t}}_{\text{Strategic complementarity}} \\ &+ \zeta\, \mathbb{1}^{\text{Tight}}_{i,t} + \text{Fixed Effects} + \varepsilon_{i,t}. \end{aligned} \tag{3.8}$$

Main regressors. The EBITDA dummy defined in Section 3.1.4 indicates whether a firm has tight financial constraints and high $\xi_{i,t}$. For robustness, I also run the same regression using the ICR dummy and the DSCR dummy.

Economically, β_0 captures the direct cost pass-through by financially unconstrained firms. β_1 is the difference between constrained and unconstrained firms, i.e., the effects of financial constraints on pass-through. Their sum, $\beta_0 + \beta_1$, is the pass-through by financially constrained firms. Similarly, γ_0 tells the strength of strategic complementarities of unconstrained firms, while γ_1 is the effect of financial constraints on strategic complementarities. Finally, I do not need to include lagged $\Delta p_{i,t}$ on the right-hand side because $\Delta p_{i,t}$ exhibits a very weak serial correlation of only -0.11 at the annual frequency. In unreported tests, I also control for lagged IVs (defined below) interacted with the dummy. Estimates are virtually unchanged.

Identification and instrumental variables. Both $\Delta mc_{i,t}$ and $\Delta p_{-i,t}$ are endogenous. For $\Delta mc_{i,t}$, the main confounder is demand shocks. Had we lived in the textbook macro model where buyers are measure-zero price takers, one buyer's demand would not affect input prices at all, and any input price change could be a valid instrument in firm-level regressions. In reality, firms are not always price takers, in which case demand shocks simultaneously affect both output and input prices. This creates an omitted variable bias problem for β_0.[16] The existence of financial constraints worsens the problem because financially constrained firms might bargain harder for lower input prices compared to unconstrained firms, which biases estimates of not only β_0 but also β_1. For $\Delta p_{-i,t}$, the main confounder is common input price shocks that affect $\Delta mc_{i,t}$ and $\Delta p_{-i,t}$ simultaneously. In AIK, the assumption is that firms often source inputs from different countries, which generates sufficient idiosyncratic variation in the foreign marginal cost component of competing firms. Unfortunately, unlike in AIK, imported goods only account for a negligible share for the majority of firms in Prowess (see Table 1). Therefore, I cannot use import price shocks as exogenous variation.

Alternatively, I exploit the fact that domestic *major input markets* defined in Section 3.1.1 are analogous to foreign markets in AIK in the following sense. First, while firms are unlikely price takers in all input markets, they should be reasonably close to price takers in domestic major input markets because there are a large number of buyers. More importantly, even if firms might not be pure price takers in major input markets, the question is to what extent it biases β_1. As I verify in Section 3.5, financial constraints are not significantly correlated with input prices. This alleviates the concern that β_1 may be biased if constrained firms can negotiate lower prices. It also alleviates the opposite concern that financial constrained firms increase prices by more because they face higher input prices.

Second, is there enough idiosyncratic variation in price changes in major input markets among competitors to instrument both $\Delta mc_{i,t}$ and $\Delta p_{-i,t}$? Prowess does not contain the identity of sellers of intermediate goods, so there is no direct answer. Following AIK, who face the same problem, I check the correlation between $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t}$ and $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{-i,t}$, which are analogous to $\Delta mc^*_{i,t}$ and $\Delta mc^*_{-i,t}$ in their paper. They find a low correlation of 0.27, whereas I find a higher correlation of 0.57 in my sample. The higher correlation is not surprising, given that firms still source in the same domestic market no matter how different their suppliers are. Given that all my results below strongly reject the underidentification test (Kleibergen-Paap rk LM statistic ≈ 40), $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{-i,t}$ still seems to have enough idiosyncratic variation to identify γ's despite the moderately higher correlation.

Given the identifying assumptions, my first two instruments are $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t}$ and $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{-i,t}$. The former is the direct contribution to firm i's marginal costs by major intermediate goods, and the latter to the competitors'. Second, I include $\Delta\rho^{\text{mj}}_{i,t}$ and $\Delta\rho^{\text{mj}}_{-i,t}$ as IVs in case price changes can be correlated among major and other inputs and that the observed cost share underestimates the loading of $\Delta\rho^{\text{mj}}$. Third, given the double interactions with the financial dummy in specification 3.8, the four IVs ($(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t}$, $\Delta\rho^{\text{mj}}_{i,t}$, $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{-i,t}$, and $\Delta\rho^{\text{mj}}_{-i,t}$) are all interacted with the financial dummy. Finally, I only include observations where major intermediate goods with price information account for 10-110% of total variable costs.[17]

[16]Strictly speaking, the bias comes from the correlation between demand shocks and markups, not prices. Yet the direction is highly ambiguous. In an ideal economy of CES demand and flexible prices, markups are uncorrelated with demand. If demand shocks change input prices but not markups, demand can actually be a valid IV for input prices. In a NK model with countercyclical markup, however, demand shocks depress markups, leading to a downward bias in pass-through. Yet in a model where demand shocks raise markups (e.g., with the Kimball aggregator), the bias goes upward.

[17]The lower bound is to ensure its relevance. I allow the upper bound to exceed 100% for three reasons. First, when input prices rise sharply, COGS tends to underestimate total variable cost under either the FIFO method (first in, first out) or the average cost method. Second, data on intermediate goods have high quality in Prowess

For robustness, I include an alternative specification in Section 3.2.2 that only exploits the idiosyncratic component in marginal cost to identify β_0 and β_1, while dropping the strategic complementarity terms altogether. The trade-offs are discussed in Section 3.2.2.

Sample restrictions. Specification 3.8 has several potential confounding factors. Crouzet and Mehrotra (2020) show that very large firms (top 1%) are less cyclical than the rest likely due to their industry scope. This can bias β_1 depending on the correlations between profit margins, size, and scope. Second, under the standard nested-CES demand system, the residual elasticity is a function of market share, and thus one would expect firms with very high market share to have much lower cost pass-through. Third, large exporters likely face a different set of competitors not included in Prowess data. Therefore, I exclude firms with very large market share (top 5%), firms with very large industry scope (top 5%), firms with either very large or very small asset size (top and bottom 5%), as well as very large exporters (top 5%). All exclusions are based on average values from $t-2$ to $t-1$.

Fixed effects, clusters, and weights. I include a battery of fixed effects as shown in Table 2. The tightest fixed effects are sector/industry-year fixed effects, which absorb any unobserved common factors such as trend inflation or inflation expectations at the sector/industry level. In principle, these fixed effects would not fit multi-sector/industry firms, but 75% of firms in the sample are single-sector and 59% are single-industry, which alleviates the concern. Importantly, I require each sector-year pair (or each industry-year pair if I use industry fixed effects) to have at least 6 firms with at least 8 years of observations in the regression sample. As a result, the median (mean) number of firms in each sector-year is 44 (55.6) and 13 (24.0) in each industry-year.

Standard errors are clustered by firm and sector-year (industry-year) when fixed effects are based on sectors (industries). In particular, firm clusters address the concern that the financial dummy is sticky at the firm level. Given that I only have 20 years, 9 sectors, and 25 industries in the sample, I do not cluster standard errors by year *and* sector/industry. Finally, regressions are weighted by average PPI-deflated sales of goods between $t-2$ and $t-1$.

Pre-determined variable assumption. Reverse causality between financial variables and prices happens when firms anticipate cost increases and adjust prices in advance. If a cost increase at t is anticipated at $t-2$, financially unconstrained firms will raise prices in advance at $t-2$, leading to (i) lower margins and worse financial ratios at $t-2$ but also (ii) smaller price changes t. Therefore, anticipated input price changes, even if exist, only bias $\hat{\beta}_1$ downwards and attenuate the estimated effects of financial constraints.

3.2.2 Idiosyncratic Cost Shocks

The identifying assumptions above are reasonable but not perfect. As mentioned, one might worry that there is no enough variation to identify γ's. Alternatively, one might worry that the IVs above may be contaminated by aggregate demand shocks. When aggregate demand shocks hit, demand for all intermediate inputs rises, driving up input prices. Even though input prices

while COGS is only a rough measure of total variable cost. Using the latter to censor the former may create more noise. Third, if firms want to accumulate inventories, their purchase of intermediate goods will naturally be higher than intermediate goods used in their COGS.

are still exogenous to firms' decisions, they are correlated with firms' demand now.

Hence in the second specification, I only use the idiosyncratic variation in input prices, obtained by removing 4-digit industry-year fixed effects from the IVs. The main advantage is that residualization cleanses common demand shocks in 4-digit industries. The main disadvantage is that it also cleanses common cost shocks, which are particularly important to macroeconomic dynamics. As shown in Alexander et al. (2024), the pass-through of idiosyncratic costs is generally different from the pass-through of common costs in a sticky-price model. Another disadvantage is that residualization absorbs over 80% of variation of $(x^{\mathrm{mj}}\Delta\rho^{\mathrm{mj}})_{-i,t}$ and $\Delta\rho^{\mathrm{mj}}_{-i,t}$, making it impossible to estimate γ's. As such, I drop strategic complementarities altogether from the new specification in equation 3.9. As before, β_1 measures the effects of financial constraints.

$$\Delta p_{i,t} = \beta_0 \Delta mc_{i,t} + \beta_1 \mathbb{1}^{\mathrm{Tight}}_{i,t} \Delta mc_{i,t} + \zeta\, \mathbb{1}^{\mathrm{Tight}}_{i,t} + \text{Fixed Effects} + \varepsilon_{i,t}. \tag{3.9}$$

Instrumental variables. For $(x^{\mathrm{mj}}\Delta\rho^{\mathrm{mj}})_{i,t}$ and $\Delta\rho^{\mathrm{mj}}_{i,t}$, I regress each on 4-digit industry-year fixed effects to obtain the residuals, $(x^{\mathrm{mj}}\Delta\rho^{\mathrm{mj}})^{\mathrm{resi}}_{i,t}$ and $(\Delta\rho^{\mathrm{mj}})^{\mathrm{resi}}_{i,t}$, respectively. The residualized IVs are then interacted with the financial dummy.

3.3 Effects of the Price Rigidity Channel on Prices

3.3.1 Effects on Current Prices

In Table 2, I report empirical results using the specifications above and find significant support for the theoretical prediction in Section 2. All instruments are strong as the F statistics are above 10.

All four columns using specification A yield virtually identical estimates. When input prices change, financially unconstrained firms have a pass-through rate of 0.64 ($\hat{\beta}_0$) in the same year. For financially constrained firms, measured by the EBITDA ratio, the cost pass-through is higher by around 0.2 percentage points ($\hat{\beta}_1$) and significant at the 1% level. In other words, financially constrained firms have a pass-through rate of 0.87 ($\hat{\beta}_0 + \hat{\beta}_1$), which is around 35% steeper than the pass-through of unconstrained firms. Next, $\hat{\beta}_0$ and $\hat{\beta}_1$ from specification B, which uses residualized IVs, show similar patterns, albeit with marginally smaller $\hat{\beta}_1$ between 0.16 and 0.20. Because specification B only uses idiosyncratic shocks, a marginally smaller $\hat{\beta}_1$ implies that $\hat{\beta}_1$ could be marginally higher during common cost shocks.

To see the robustness of my estimates, I use the ICR and DSCR instead of the EBITDA ratio in Tables A3 and A4. Point estimates of β_0 and β_1 using specification A are highly similar, though the significance deteriorates when I use the DSCR. For specification B, both give lower $\hat{\beta}_1$ between 0.11 and 0.14. Lower $\hat{\beta}_1$ in turn also replies potentially higher $\hat{\beta}_1$ during common cost shocks. In short, three different measures all give supporting evidence for corollary 1.

Interestingly, strategic complementarities show opposite patterns in Table 2: financially constrained firms have much weaker strategic complementarities compared to unconstrained firms. Financially unconstrained firms have $\hat{\gamma}_0$ around 0.35, slightly lower than but roughly in line with the 0.5 estimated by Amiti et al. (2019). For financially unconstrained firms, however,

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable: $\Delta p_{i,t}$			Spec A		Spec B	
$\Delta mc_{i,t}$ ($\hat{\beta}_0$)	0.64^{***}	0.64^{***}	0.63^{***}	0.62^{***}	0.69^{***}	0.67^{***}
	(0.05)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)
Tight × $\Delta mc_{i,t}$ ($\hat{\beta}_1$)	0.23^{***}	0.20^{**}	0.24^{***}	0.27^{***}	0.20^{***}	0.16^{***}
	(0.08)	(0.09)	(0.08)	(0.08)	(0.05)	(0.05)
$\Delta p_{-i,t}$ ($\hat{\gamma}_0$)	0.35^{***}	0.35^{***}	0.29^{***}	0.36^{***}		
	(0.08)	(0.09)	(0.09)	(0.13)		
Tight × $\Delta p_{-i,t}$ ($\hat{\gamma}_1$)	-0.26^{**}	-0.24^{**}	-0.26^{**}	-0.29^{***}		
	(0.10)	(0.11)	(0.10)	(0.11)		
Tight	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.01^{***}	0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y				
Sector FE	Y					
Industry FE		Y				
Sector-Year FE			Y		Y	
Industry-Year FE				Y		Y
R^2	0.729	0.732	0.688	0.671	0.689	0.680
N	9,738	9,065	9,738	9,065	9,738	9,065
Firms	826	797	826	797	826	797
Two-digit Sectors	9		9		9	
Four-digit Industries		25		25		25
Weak IV F-test						
Cragg-Donald	64.65	59.32	65.63	58.30	244.00	222.98
Kleibergen-Paap	15.05	14.11	15.09	10.00	27.36	25.71
Hansen J-test χ^2	2.896	2.447	5.409	2.993	5.051	1.730
p value	0.575	0.654	0.248	0.559	0.080	0.421
Financial Amplification						
$\hat{\beta}_0 + \hat{\beta}_1$	0.88***	0.85***	0.87***	0.88***	0.89***	0.82***
$\hat{\gamma}_0 + \hat{\gamma}_1$	0.09	0.11	0.03	0.07		

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

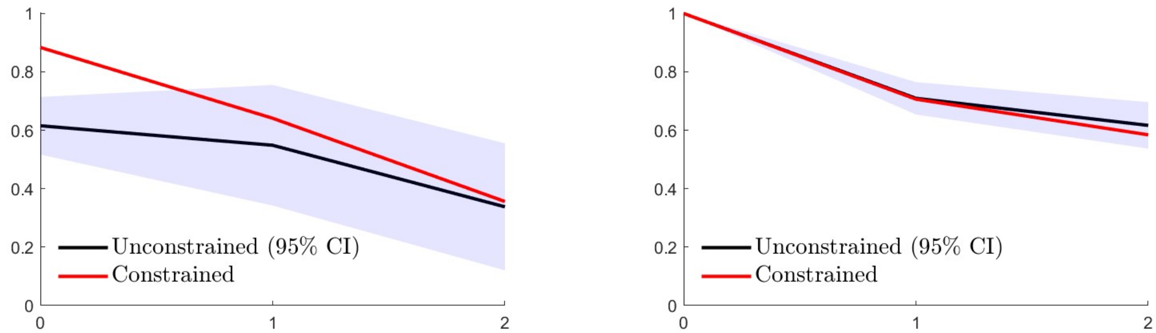
Notes: "Low EBITDA" ("High EBITDA") refers to the bottom 25th (top 75th) percentile in the regression sample. All regressions are weighted by average PPI-deflated sales of goods between $t-2$ and $t-1$. The median (mean) number of years per firm is 11 (11.8). The median (mean) number of firms in each sector-year is 44 (55.6) and 13 (24.0) in each industry-year. First-stage results are in Table xxx. Standard errors are clustered by firm and sector-year in columns 1, 3, 5, and by firm and industry-year in columns 2, 4, 6.

Table 2: Effects of Financial Constraints on Current Prices

their strategic complementarities ($\hat{\gamma}_0 + \hat{\gamma}_1$) are indistinguishable from zero. The same result also shows up in Tables A3 and A4 with strong significance when I use alternative financial measures. This empirical pattern is consistent with the second case discussed in proposition 2 where competitors affect demand elasticity only with a time lag.

3.3.2 Effects on Future Prices

In addition to the effects on current prices, I examine the effects on future prices. Financially unconstrained firms, given price adjustment costs, should opt for a smoother path of price



(a) Marginal Cost Pass-through

(b) Persistence of Input Cost Shocks

Notes: All estimates are from regressions using the EBITDA dummy and industry-year fixed effects. Panel (a) is the visualization of column (4) of Table 2 and column (2) of Table A7. Panel (b) is the visualization of column (2) of Table A11.

Figure 1: Pass-through and Input Costs Over Time

adjustments compared to their financially constrained peers. Thus, the difference in pricing should be the strongest upon the shock and fade away over time. If differences are persistent, then the price rigidity channel should be rejected.

In Table A7 I show the cumulative effects on prices after one year ($\sum_{h=0}^{1} \Delta p_{i,t+h}$) and two years ($\sum_{h=0}^{2} \Delta p_{i,t+h}$) using all three financial measures. For better visualization, I plot in panel (a) of Figure 1 how $\hat{\beta}_0$ and $(\hat{\beta}_0 + \hat{\beta}_1)$ evolve from $t = 0$ to $t = 2$ using specification A with the EBITDA dummy and industry-time fixed effects. $\hat{\beta}_0$ for financially unconstrained firms remain similar from $t = 0$ to $t = 1$ and decline gradually at $t = 2$, consistent with the price smoothing prediction. Furthermore, cumulative differences between constrained and unconstrained firms ($\hat{\beta}_1$ and $\hat{\gamma}_1$) lose both significance and magnitude after one year across all specifications. After two years, $\hat{\beta}_1$ even turns insignificantly negative in some specifications. Given that $\hat{\beta}_1$ is significantly positive at $t = 0$, it means that financially constrained firms substantially reverse their price increases at $t = 1$, which is the opposite of what a sticky price firm would normally do.

The results also alleviate the concern that annual data might not be frequent enough to test sticky price models. If price rigidities are so low that the price rigidity channel is effective only in the first few quarters and largely dissipates within one year, the significant differences observed in Section 3.3.1 should reflect some permanent heterogeneity between the two groups. Then it will be difficult to explain the partial reversal at $t = 1$. In addition, as I will show in Section 3.5, the difference in pricing is also not driven by differences in input cost shocks.

Finally, $\hat{\gamma}_0$ becomes significantly positive at $t = 2$, meaning that both financially constrained and unconstrained firms respond to competitor prices with a lag. This also appears consistent with the dynamic elasticity case discussed in proposition 2, and future research is needed to provide more empirical evidence.

3.3.3 Non-binary Interactions

The binary dummy used above is easy to interpret but inevitably coarse. In particular, when financial constraints are one-sided as in many models, their effects should also be one-sided, i.e., financially unconstrained firms should have the same cost pass-through no matter how unconstrained they are. To test this hypothesis, I split the financial variable into four quartiles, of which the lowest coincides with the $\mathbb{1}^{\text{Tight}}_{i,t}$ dummy in specifications 3.8 and 3.9. Then I set the lowest quartile as the reference group and interact the other three quartiles with $\Delta mc_{i,t}$ and $\Delta p_{-i,t}$, as shown in specification 3.10.

The interpretation of coefficients in specification 3.10 is straightforward. In particular, β_1^* is the same as $\beta_0 + \beta_1$ in specification 3.8 given the choice of the reference group. β_2^*, β_3^*, and β_4^* are the difference between the reference group (most financially constrained) and the second, third, and fourth quartiles, respectively. If the effects of financial constraints are indeed one-sided, β_2^*, β_3^*, and β_4^* should be negative but not monotone. The interpretation of γ^*'s and ζ^*'s is similar.

$$
\begin{aligned}
\Delta p_{i,t} = {} & \beta_1^* \Delta mc_{i,t} + \beta_2^* \mathbb{1}^{(25^{\text{th}},50^{\text{th}}]}_{i,t} \Delta mc_{i,t} + \beta_3^* \mathbb{1}^{(50^{\text{th}},75^{\text{th}}]}_{i,t} \Delta mc_{i,t} + \beta_4^* \mathbb{1}^{\geq 75^{\text{th}}}_{i,t} \Delta mc_{i,t} \\
& + \gamma_1^* \Delta p_{-i,t} + \gamma_2^* \mathbb{1}^{(25^{\text{th}},50^{\text{th}}]}_{i,t} \Delta p_{-i,t} + \gamma_3^* \mathbb{1}^{(50^{\text{th}},75^{\text{th}}]}_{i,t} \Delta p_{-i,t} + \gamma_4^* \mathbb{1}^{\geq 75^{\text{th}}}_{i,t} \Delta p_{-i,t} \\
& + \zeta_2^* \, \mathbb{1}^{(25^{\text{th}},50^{\text{th}}]}_{i,t} + \zeta_3^* \mathbb{1}^{(50^{\text{th}},75^{\text{th}}]}_{i,t} + \zeta_4^* \mathbb{1}^{\geq 75^{\text{th}}}_{i,t} + \text{Fixed Effects} + \varepsilon_{i,t}.
\end{aligned} \tag{3.10}
$$

Table A5 shows the results using all three financial variables. As expected, $\hat{\beta}_1^*$ is virtually the same as $\hat{\beta}_0 + \hat{\beta}_1$ across specifications in Tables 2, A3, and A4. While the Kleibergen-Paap F statics are generally much weaker in Table A5, that $\hat{\beta}_1^*$ is consistent across tables slightly alleviates concerns about spurious estimates. That being said, one should take a grain of salt when interpreting the results.

Importantly, in none of the 12 regressions does cost pass-through exhibit monotonicity (monotonicity means $0 > \hat{\beta}_2^* > \hat{\beta}_3^* > \hat{\beta}_4^*$). When I use the EBITDA ratio in columns (1)-(4), $\hat{\beta}_3^*$ and $\hat{\beta}_4^*$ (the two least constrained groups) are almost identical. $\hat{\gamma}_4^*$ is larger than $\hat{\gamma}_3^*$ but the difference is not statistically significant. When I use the ICR and the DSCR in columns (5)-(12), $\hat{\beta}_2^*$ is roughly the same as $\hat{\beta}_3^*$, while $\hat{\beta}_4^*$ is very noisy and insignificant. One potential reason for the insignificant $\hat{\beta}_4^*$ is that the highest ICR/DSCR quartile may include some highly constrained firms that borrow only very little. If a firm has little access to credit, the denominator in the ICR and the DSCR will be close to zero, leading to spuriously high ratios.[18] Overall, results in Table A5 suggest that the price rigidity channel is one-sided as expected, and the use of the binary dummy does not conceal any important heterogeneity in the unconstrained group.

[18] In Figure A3, I plot the distribution of leverage (after removing time-industry medians). In each panel, I partition the regression sample evenly into 16 groups by their EBITDA, ICR, or DSCR and show the box plot for each group. In panel (a), leverage appears stable among high-EBITDA groups. By contrast, firms with the highest ICR or DSCR in panels (b) and (c) have much lower leverage, consistent with the hypothesis that some firms in this group are indeed constrained and have little access to credit.

3.3.4 Pass-through of Large Cost Increases

Next, I check whether the effects of financial constraints differ during large cost increases. When cost increases are large, financially constrained firms face even greater pressure on their margins, therefore they should move even closer to complete cost pass-through. The new specification for testing this hypothesis includes a new dummy, $\mathbb{1}_{i,t}^{\text{Large}}$, for large cost increases on top of the double interactions in equation 3.8.[19] To calculate the dummy, I first remove industry medians from $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t}$ to obtain $(x^{\text{mj}}\Delta\rho^{\text{mj}})^{*}_{i,t}$. Next, I assume that a firm faces large cost increases ($\mathbb{1}_{i,t}^{\text{Large}} = 1$) when $(x^{\text{mj}}\Delta\rho^{\text{mj}})^{*}_{i,t}$ exceeds the 70th percentile (3.5%) in the regression sample. During large cost increases, financially constrained firms account for around 32% of observations in the sample.

The two dummy variables create four groups of firms: financially constrained (unconstrained) firms with large cost increases (normal cost changes). Next, I create a dummy for each of the four firm groups and estimate β and γ for each group using specification 3.12. For instance, $\beta^{\text{T,L}}$ and $\gamma^{\text{T,L}}$ characterize the pricing behavior of financially constrained firms during large cost increases. Note that specification 3.12 is econometrically identical to the usual triple interaction specification, though I find it easier to interpret β's and γ's this way.[20]

$$
\begin{aligned}
\Delta p_{i,t} = {} & \beta^{\text{T,L}}\, \mathbb{1}_{i,t}^{\text{Tight, Large}} \Delta mc_{i,t} && + \beta^{\text{NT,L}}\, \mathbb{1}_{i,t}^{\text{Not Tight, Large}} \Delta mc_{i,t} \\
& + \beta^{\text{T,NL}}\, \mathbb{1}_{i,t}^{\text{Tight, Not Large}} \Delta mc_{i,t} && + \beta^{\text{NT,NL}}\, \mathbb{1}_{i,t}^{\text{Not Tight, Not Large}} \Delta mc_{i,t} \\
& + \gamma^{\text{T,L}}\, \mathbb{1}_{i,t}^{\text{Tight, Large}} \Delta p_{-i,t} && + \gamma^{\text{NT,L}}\, \mathbb{1}_{i,t}^{\text{Not Tight, Large}} \Delta p_{-i,t} \\
& + \gamma^{\text{T,NL}}\, \mathbb{1}_{i,t}^{\text{Tight, Not Large}} \Delta p_{-i,t} && + \gamma^{\text{NT,NL}}\, \mathbb{1}_{i,t}^{\text{Not Tight, Not Large}} \Delta p_{-i,t} \\
& + \zeta_1\, \mathbb{1}_{i,t}^{\text{Tight}} + \zeta_2\, \mathbb{1}_{i,t}^{\text{Large}} + \zeta_3\, \mathbb{1}_{i,t}^{\text{Tight}} \mathbb{1}_{i,t}^{\text{Large}} + \text{Fixed Effects} + \varepsilon_{i,t}. &&
\end{aligned} \tag{3.12}
$$

Table A6 presents the results. Again, the low Kleibergen-Paap F statistics calls for additional caution when interpreting the results. For financially unconstrained firms, direct cost pass-through varies very little regardless of the magnitude of the cost increase. Strategic complementarities are also similar across specifications, ranging from 0.3 to 0.4, although point estimates are mildly larger and more significant during large cost increases. Interestingly, this suggests that state-dependent pricing does not play a substantial role in my results.

Financially constrained firms exhibit the highest cost pass-through during large cost increases—most point estimates of $\beta^{\text{T,L}}$ fall between 0.95 and 1 across specifications, which are around 40-

[19] Notice that specification 3.9 is not suitable for studying nonlinear effects of large cost increases because residualization already assumes linearity.

[20] Equation 3.11 shows the triple interaction specification. For instance, $\beta^{\text{T,L}}$ in specification 3.12 is the same as $(\beta_0 + \beta_1 + \beta_2 + \beta_3)$, $(\beta^{\text{T,L}} - \beta^{\text{NT,L}}) = \beta_1 + \beta_3$, and $\beta_3 = (\beta^{\text{T,L}} - \beta^{\text{NT,L}}) - (\beta^{\text{T,NL}} - \beta^{\text{NT,NL}})$.

$$
\begin{aligned}
\Delta p_{i,t} = {} & \beta_0 \Delta mc_{i,t} + \beta_1 \mathbb{1}_{i,t}^{\text{Tight}} \Delta mc_{i,t} + \beta_2 \mathbb{1}_{i,t}^{\text{Large}} \Delta mc_{i,t} + \beta_3 \mathbb{1}_{i,t}^{\text{Tight}} \mathbb{1}_{i,t}^{\text{Large}} \Delta mc_{i,t} \\
& + \gamma_0 \Delta p_{-i,t} + \gamma_1 \mathbb{1}_{i,t}^{\text{Tight}} \Delta p_{-i,t} + \gamma_2 \mathbb{1}_{i,t}^{\text{Large}} \Delta p_{-i,t} + \gamma_3 \mathbb{1}_{i,t}^{\text{Tight}} \mathbb{1}_{i,t}^{\text{Large}} \Delta p_{-i,t} \\
& + \zeta_1\, \mathbb{1}_{i,t}^{\text{Tight}} + \zeta_2\, \mathbb{1}_{i,t}^{\text{Large}} + \zeta_3\, \mathbb{1}_{i,t}^{\text{Tight}} \mathbb{1}_{i,t}^{\text{Large}} + \text{Fixed Effects} + \varepsilon_{i,t}.
\end{aligned} \tag{3.11}
$$

60% steeper than $\hat{\beta}^{\text{NT,L}}$. The difference is significant at the 1% level for all specifications using the EBITDA ratio and between the 1% and 5% levels for those using the ICR. The significance deteriorates when I switch to the DSCR: only two out of four regressions report significant differences, although point estimates are still similar.

During normal cost changes, cost pass-through ($\hat{\beta}^{\text{T,NL}}$) is only significantly higher for constrained firms in columns (3) and (4) when I use the EBITDA ratio. When I use the ICR and DSCR, $\hat{\beta}^{\text{T,NL}}$ is no different from $\hat{\beta}^{\text{NT,NL}}$, meaning that there is little difference in pass-through during normal times. However, one needs to interpret the results with a grain of salt because $(\hat{\beta}^{\text{T, L}} - \hat{\beta}^{\text{NT, L}}) - (\hat{\beta}^{\text{T, NL}} - \hat{\beta}^{\text{NT, NL}})$, the difference in pass-through differentials, is only significant when I use the ICR in columns (6)-(8). Finally, financially constrained firms show no significant strategic complementarities regardless of the shock size, though point estimates appear closer to zero during large cost increases.

3.4 Effects of the Price Rigidity Channel on Non-price Variables

Having shown the effects on prices, now I show the effects on important non-price variables to validate my theoretical model.

Profit margins. First and foremost, I examine the effects on profit marginals, which play a pivotal role in the theoretical model. The theory predicts that financially constrained firms should be able to mitigate the negative impact on their profit margins through raising current prices.

First, I check the COGS margin. The COGS margin, calculated as sales over COGS, is the most primitive measure of profitability.[21] In the empirical analysis, I use log changes in the COGS margin, i.e., $\Delta \ln \frac{\text{Sales}_{i,t}}{\text{COGS}_{i,t}}$, as the dependent variable. I report the results in Panel (a) of Table A8. Both constrained and unconstrained firms see significantly lower COGS margins when costs rise, but the impact on constrained firms is significantly smaller. After a 1% increase in marginal costs, the COGS margin of unconstrained firms drops by around 0.35 percentage points ($\hat{\beta}_0$), while the COGS margin of constrained firms drops by less than 0.2 percentage points ($\hat{\beta}_0 + \hat{\beta}_1$). The difference is significant at the 1% level when I use the EBITDA dummy, the 5% level when I use the ICR dummy, and 10% when I use the DSCR dummy.

Next, I check the EBITDA margin, a more comprehensive measure of profitability than the COGS margin. Similar to the COGS margin, the EBITDA margin is defined as sales over sales minus EBITDA, which avoids the problem of taking the log of negative EBITDA. Panel (b) of Table A8 shows the results using $\Delta \ln \frac{\text{Sales}_{i,t}}{\text{Sales}_{i,t} - \text{EBITDA}_{i,t}}$. After a 1% increase in marginal costs, the EBITDA margin of unconstrained firms drops by 0.2 percentage points, while for constrained firms I find $\hat{\beta}_0 + \hat{\beta}_1 \approx 0$ across all specifications, meaning that they manage to keep their EBITDA

[21] Note that sales-to-COGS is identical to manufacturing sales-to-TVC by the definition of TVC in Section 3.1.3. Following equation 3.7 and the assumptions behind it, one can also equalize log changes in the COGS margin and log changes in markup:

$$\Delta \ln \frac{\text{Sales}_{i,t}}{\text{COGS}_{i,t}} = \Delta \ln \frac{\text{Mfg. Sales}_{i,t}}{\text{TVC}_{i,t}} = \Delta \ln \frac{P_{i,t} Y_{i,t}}{\text{TVC}_{i,t}} = \Delta \left(p_{i,t} - mc_{i,t}^{\text{nom.}} \right).$$

For this reason, I write the COGS margin as $\frac{\text{Sales}}{\text{COGS}}$ instead of $\frac{\text{Sales}-\text{COGS}}{\text{Sales}}$.

margin unaffected despite the cost increase. However, the difference ($\hat{\beta}_1$) is less significant than in Panel (a). $\hat{\beta}_1$ is still significant at the 1% to 5% level when I use the ICR dummy and the DSCR dummy, but it sometimes turns insignificant when I use the EBITDA dummy. The weakened significance is potentially because the EBITDA margin consists of more items not directly related to production.

Overall, results in Table A8 confirm the theoretical prediction that financially constrained firms increase their cost pass-through to improve short-term profitability and internal cash flows.

Output. To test the dynamic effects on output, I use specifications A and B and replace the dependent variable with cumulative output changes up to one year. Output is defined in equation 3.2. Table A9 reports the empirical results. When marginal costs rise by 1%, financially unconstrained firms lose output by 0.3-0.4% ($\hat{\beta}_0$) at $t = 0$, and estimates are significant at the 1% level. The loss of output remains largely unchanged at $t = 1$. For financially constrained firms, however, I fail to obtain any precise estimates. $\hat{\beta}_1$ appears insignificant in most specifications. Some estimates of β_1 in panel (a) are even insignificantly positive. One potential reason is that estimates are noisy and suffer from the multicollinearity problem, which might also explain why $\hat{\gamma}_1$ in the same regressions also have the wrong sign. Another reason could be that financially constrained firms may spend more efforts finding new buyers when their prices are not competitive. Only in columns (11) and (12) of panel (b) I find significantly negative effects on cumulative output from $t = 0$ to $t = 1$, consistent with the theoretical prediction that higher prices set by financially constrained firms lower demand.

Leverage. Finally, I examine how leverage evolves after cost increases. Intuitively, credit demand should increase as firms want to borrow to smooth cash flows. If firms are financially unconstrained, higher credit demand should lead to higher leverage either through borrowing more or through repaying less. Constrained firms, on the contrary, should prefer raising internal cash flows over increasing leverage.

Table A10 shows the effects on leverage.[22] Since the debt-to-assets ratio is often skewed, I use the log transformation, $\ln\left(1+\frac{\text{Debt}_{i,t}}{\text{Assets}_{i,t}}\right)$, instead. Unconstrained firms show no change in leverage after cost increases. By contrast, constrained firms choose to deleverage. Estimates are particularly significant when I use the ICR but largely insignificant when I use the EBITDA ratio.

3.5 Robustness Checks

Input costs. Price changes result from changes either in the pass-through rate or in input costs, so it is necessary to check if input cost increases persist in the same way for financially constrained and unconstrained firms. In Table A11, I calculate the persistence of major input price changes for the two types. The first row is the persistence estimated for financially unconstrained firms. One year after an initial input cost increase, 71-76% remains. After two years, it decays to 61%. The second row is the difference in persistence for financially constrained

[22]Debt is measured by the "Borrowing" variable in Prowess, which includes all borrowings from banks, bonds, other companies, etc. Unfortunately, it does not distinguish the current and non-current portions of borrowings for data before 2011, and I cannot test the effects on debt by maturity.

firms. For most specifications, the difference is almost exactly zero and insignificant, suggesting no meaningful difference in shock persistence. The only two exceptions are column (1), where constrained firms have slightly higher persistence, and column (10), where constrained firms have slightly lower persistence. For better visualization, I plot the persistence by firm type using estimates from column (2) in Panel (b) of Figure 1. Given results in other specifications, it is more likely that the two exceptions are false positives than that all others are false negative.

Firm size. As discussed in Section 3.1.6, my financial dummies are all correlated with firm size. Strictly speaking, it is unclear how such a correlation would *a priori* affect my results. On the one hand, size is often used as a proxy for financial constraints in the literature, which indeed helps identify financially constrained firms. On the other hand, large firms have lower residual elasticity in usual variable markup models, higher steady-state markups, and thus higher steady-state EBITDA ratios. Lower residual elasticity also leads to a flatter FOC slope per equation 2.14. Therefore, even without financial frictions, one might still observe that low-EBITDA firms have higher cost pass-through.

Two robustness checks help alleviate this concern. First, effects of financial constraints do not lead to a permanent price gap as shown in Section 3.3.2. If size were the main driver, it should generate permanent heterogeneity as size is a higher persistent characteristic.

Second, in Table A12, I run a new regression with two double interaction terms: one with the financial dummy and the other with a "small-size" dummy. A firm is considered small if its asset size is below the 25th percentile after removing year fixed effects. The new specification reveals more information at the expense of the F statistics, and one should take a grain of salt with the estimates. That being said, estimates for financially unconstrained and non-small firms are even closer to estimates in Amiti et al. (2019). Their cost pass-through ($\hat{\beta}_0$) and strategic complementarities ($\hat{\gamma}_0$) are both around 0.5 and 0.5. Next, as expected, small firms have higher pass-through and lower strategic complementarities. Last but not the least, financially constrained firms continue to have higher pass-through ($\hat{\beta}_1$) and lower strategic complementarities ($\hat{\gamma}_1$) even after controlling for size in most specifications. When I use the EBITDA dummy, $\hat{\beta}_1$ and $\hat{\gamma}_1$ are virtually unchanged compared to Table 2. Meanwhile, $\hat{\beta}_0$ is lower in specification A, meaning that in percentage terms the pass-through of financially constrained firms is even steeper. Finally, $\hat{\beta}_1$ becomes generally weaker when I use the ICR and DSCR dummies. However, whenever $\hat{\beta}_1$ is weaker, the interaction with the size dummy is even weaker. If size were what drives my results, we would expect the interaction with size to be much stronger than the interaction with the financial dummy. A more plausible explanation is that the ICR and the DSCR are noiser than EBITDA. As such, when I use the ICR/DSCR, $\hat{\beta}_1$ is more likely to be diluted by size, which is also correlated with financial constraints.

4 The Price Rigidity Channel in A New Keynesian Model

Empirical results lend strong support to the theoretical prediction that tight financial constraints amplify direct cost pass-through with high nonlinearity. During large shocks, direct cost pass-through can be over 50% higher for 25% of firms that are classified as "low-EBITDA," suggesting quantitatively important aggregate implications. In this section, I embed the price rigidity channel into a textbook New Keynesian model to analyze its general equilibrium implications.

4.1 Baseline Model

4.1.1 Firms

The intermediate goods sector is the same as the model in Section 2 except for one extension. To ensure asset market clearing, i.e., that debt is net zero in aggregate, I introduce a non-monetary quadratic debt adjustment cost that centers debt around zero.

$$\mathscr{L}_{i,t} = \frac{\tau_d}{2} D_{i,t}^2 P_t Y_t. \tag{4.1}$$

The debt target rule provides an additional free parameter, τ_d, which compensates for the fact that β is not a free parameter here. In the HANK literature, one often chooses the discount factor β to adjust household borrowing to zero in the steady state. By contrast, on the firm side, β directly enters the Phillips curve and therefore cannot be chosen arbitrarily. To not distort the Phillips curve, I set β at 0.98, a fairly conventional value, while solely using τ_d to clear the asset market.

4.1.2 Households

A representative household chooses consumption C_t, labor supply N_t, and bond holdings B_t to maximize her lifetime utility, $\sum_{h=0}^{\infty} \beta^h \left(\frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\psi}}{1+\psi} \right)$, subject to a budget constraint $P_t C_t + Q_t B_t = B_{t-1} + W_t^h N_t + T_t$. B_t is risk-free bonds, of which the price is Q_t. W_t^h is the nominal wage received by households. T_t is the profits from firms net of any government transfers. Consumption C_t is defined by a standard CES aggregator: $C_t = \left(\int_0^1 C_{i,t}^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}$.

Since all adjustment costs are non-monetary costs, in equilibrium $C_t = Y_t$. On top of the household's Euler equation, I introduce a generic demand shock ν_t in the IS curve in equation 4.2. ν_t can come from a variety of sources, such as shocks to the discount factor β, shocks to interest rates, or shocks to households' inflation expectations.

$$Y_t^{-\frac{1}{\sigma}} = \mathrm{E}_t \beta e^{(i_{t+1} - \pi_{t+1} + \nu_t)} Y_{t+1}^{-\frac{1}{\sigma}}, \tag{4.2}$$

Notice that i_{t+1} is the risk-free rate at t, and $i_{t+1} = -\ln Q_t$ in equilibrium. Both i_{t+1} and π_t are defined in log changes instead of in percentage changes.

4.1.3 Flexible Wages

To isolate the effects on pricing from other frictions, I assume flexible wages as in the textbook three-equation model. Had I introduced sticky wages, firms would see even lower profitability during negative shock because wages cannot fall. This would tighten financial constraints and steepen the Phillips curve in my model.

4.1.4 Others

The model has a fully competitive retail sector. The central bank sets the policy rate i_{t+1}, which is the risk-free rate at t, according to a Taylor rule:

$$i_{t+1} = \phi_\pi \pi_t + \phi_y \hat{y}_t + \ln \beta. \tag{4.3}$$

$\hat{y}_t$ is the deviation of y_t from the steady state value.[23] There is no fiscal policy. Markets clear when $C_t = Y_t$, $D_t = 0$, and $N_t = L_t$.

4.1.5 Aggregation

Aggregate prices. Individual prices $P_{i,t}$ are given by equation B.1 in Section 2.1. Prices are then aggregated according to $P_t = \left(\int_0^1 P_{i,t}^{1-\epsilon} di\right)^{\frac{1}{1-\epsilon}}$. Define $\tilde{P}_{i,t} = \frac{P_{i,t}}{P_t}$ as the deviation from the aggregate price.

Labor demand. Define aggregate $A_t = \left(\int_0^1 A_{i,t}^{\epsilon-1} di\right)^{\frac{1}{\epsilon-1}}$, $\tilde{A}_{i,t} = \frac{A_{i,t}}{A_t}$, and $\omega = \left(\int_0^1 \omega_i^{\epsilon-1} di\right)^{\frac{1}{\epsilon-1}}$. Aggregate labor demand is given by:

$$L_t = \left(\frac{Y_t + \omega}{A_t}\right)^{\frac{1}{1-\gamma}} \int_0^1 \left[\frac{\tilde{A}_{i,t}^{-1}}{Y_t + \omega}\left(\tilde{P}_{i,t}^{-\epsilon} Y_t + \omega_i\right)\right]^{\frac{1}{1-\gamma}} di. \tag{4.4}$$

Let $\Delta_t = \int_0^1 \left[\frac{\tilde{A}_{i,t}^{-1}}{Y_t+\omega_i}\left(\tilde{P}_{i,t}^{-\epsilon} Y_t + \omega\right)\right]^{\frac{1}{1-\gamma}} di$, which measures the effect of price dispersion on labor usage.

Aggregate wage. From the Household FOC we have $w_t^h - p_t = \sigma c_t + \psi n_t$. In equilibrium, $n_t = l_t = \frac{1}{1-\gamma}[\ln(Y_t + \omega) - a_t] + \delta_t$, where $\delta_t = \ln \Delta_t$. The real wage paid by firms in the flexible-wage equilibrium is thus given by

$$w_t - p_t = \sigma y_t + \frac{\psi}{1-\gamma} \ln(Y_t + \omega) - \frac{\psi}{1-\gamma} a_t + \psi \delta_t. \tag{4.5}$$

4.1.6 Calibration and the Solution Method

Table 3 summarizes the calibration of all parameters. For all non-financial parameters (i.e., all except ϕ, and τ_e), I use conventional values in the literature. I choose τ_p such that the slope of the margin cost Phillips curve for unconstrained firms, $\frac{\epsilon_{i,t}-1}{\tau_p}$, equals 0.02. For the fixed cost ω, I set it at 0.25 for the benchmark model, in line with the estimate in Abraham et al. (2024). For the earnings-based borrowing constraint, I set ϕ at 4. In the DealScan-Compustat sample, the medium debt-to-EBITDA ratio is around 16 for quarterly EBITDA (or 4 for annual EBITDA), and

[23] In the heterogeneous firm model, it is easier and thus more practical to target the gap from the steady state rather than targeting the gap from the efficient-level output. Since my main interest is on *supply-side* shocks, the choice of the output gap is trivial.

Parameter		Value
Discount factor	β	0.98
IES	σ	1
Labor supply elasticity	ψ	5
Demand elasticity	ϵ	6
Return to scales	γ	0.25
Rotemberg adj. cost	τ_p	250
Idio. shock variance	σ_a	0.05
Idio. shock persistence	ρ_a	0.95
Fixed cost	ω	0.25
Borrowing constraint	ϕ	4
Debt adj. cost	τ_d	0.5
Equity issuance cost	τ_e	5
Taylor rule for π_t	ϕ_π	1.5
Taylor rule for $\hat{y}_t$	ϕ_y	0.125

Table 3: Calibration of the Benchmark Model

the medium slack is 3.8 (or 0.96 for annual EBITDA). Since I have neither investment nor term loans in the model, the debt-to-EBITDA ratio is not directly comparable, and slack is a more appropriate metric.[24] Lastly, I calibrate τ_e to be 5 to reflect the difficulty to issue equity quickly. In the steady state, the economy has an average markup of 21.1% and an average EBITDA-to-sales ratio of 22.1%. Given that net debt is zero in the steady state, the average profit-to-sales ratio and the dividend-to-sales ratio are also 22.1%.[25]

I solve the nonlinear transitional dynamics in the sequence space using the quasi-Newton method described in Section 6 of Auclert et al. (2021). Details of the algorithm are described in Capelle and Liu (2023).

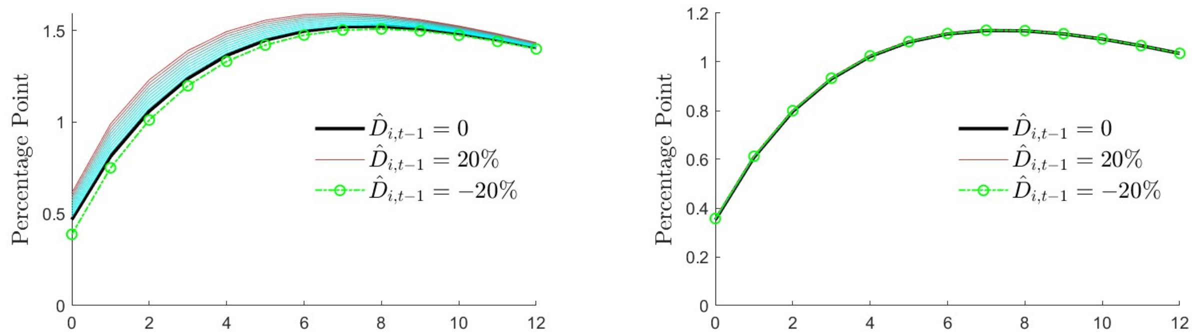
4.2 Price Responses in Partial Equilibrium

I first verify the partial-equilibrium mechanisms of my model. In panel (a) of Figure 2, I impose a negative idiosyncratic shock of one standard deviation to the benchmark model. The black line is the price response evaluated at the steady state. To see how financial constraints affect prices in the model, I vary the pre-shock debt level and compare the responses. As I increase the debt level from 0% of steady-state sales (blue thin lines) to 20% (red thin lines), price responses are amplified by over 31.0% (12.3%) in one quarter (one year). The exact degree of amplification, of course, may vary a lot depending on the calibration.

Second, the amplification is asymmetric in indebtedness, consistent with my empirical findings in Section 3.3.3. If I lower the pre-shock debt level (green line with circle markers), the firm immediately cashes out the windfall as dividends, and its price response remains almost unchanged. The amplification is also asymmetric in the sign of the shock. If I impose a positive productivity shock (results not plotted), the difference caused by the pre-shock debt level be-

[24] Data available at https://wrds-www.wharton.upenn.edu/. Details available upon request.

[25] Note that profits and dividends appear high because the model does not have capital. In a model with capital, one would subtract the cost of capital from profits, and then profits would be lower.



(a) Benchmark Model (b) Unconstrained Model

Notes: Debt $\hat{D}_t$ is normalized by steady state sales.

Figure 2: Firm-level Prices ($\hat{p}_{i,t}$) After An Idiosyncratic Shock

comes largely negligible.

Third, the benchmark model replicates the non-linearity in shock size in Section 3.3.4. If I increase the shock size from 1 to 2 standard deviations (results not plotted), the price response is amplified by 75.1% (27.6%) in one quarter (one year) for firms with pre-shock debt equal to 20% of steady-state sales.

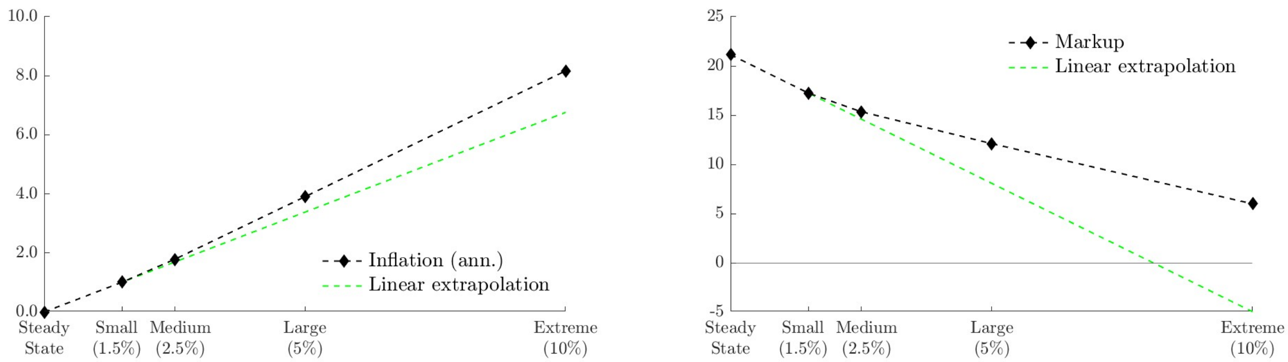
In panel (b), I introduce an unconstrained model for comparison. The unconstrained model has zero fixed cost ($\omega = 0$). As a result, firms have ample cash flows, and the financial constraints never bind. As expected, price responses show no noticeable changes as I vary the pre-shock debt level.

4.3 Inflation Dynamics in General Equilibrium

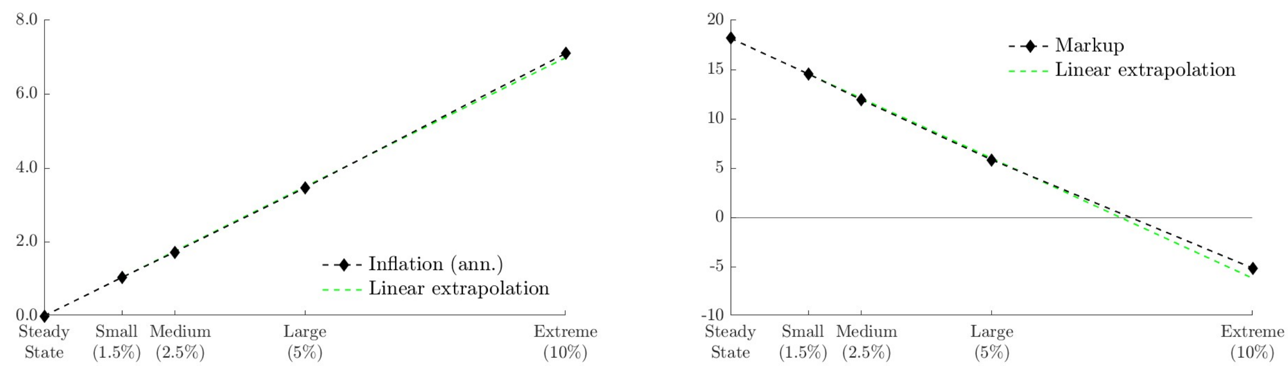
Moving from partial equilibrium to general equilibrium, I impose aggregate shocks to the model and investigate the inflation responses. Generally, any shock that squeezes internal cash flows can trigger the same price rigidity channel. These shocks include most supply-side shocks such as cost-push shocks, productivity shocks, and hiring cost shocks.[26] As such, I only show results for aggregate productivity shocks in this section.

In Figure 3, I show how inflation and the aggregate markup respond upon impact after different productivity shocks. All shocks follow an AR(1) process with a persistence parameter of 0.7, and their initial sizes range from 1.5% (small) to 10% (extreme). The black diamonds are simulated results, whereas the dotted green line is the linear extrapolation of the response after a small shock. The deviation of the simulated results from the linear extrapolation quantifies

[26] Among all supply-side shocks, only pure markup shocks can increase profits. However, pure markup shocks are rare, and the term "markup" shock usually refers to marginal cost shocks that cannot be mapped to the output gap. The role of demand shocks is less clear because profit cyclicality (conditional on demand shocks) largely depends on parameter configurations unrelated to the pricing problem I study in this paper. For instance, wage rigidities have been proven important in usual medium-scale DSGE models. To keep the mechanism clear, I focus on supply-side shocks that generate unambiguously procyclical profits. Qualitatively, my findings can be generalized to negative demand shocks if wages are sufficiently sticky.



(a) Benchmark Model



(b) Unconstrained Model

Notes: All variables are in percentage points. Inflation is annualized. Linear extrapolation is based on results after a small productivity shock.

Figure 3: Inflation and the Aggregate Markup Upon Impact

the nonlinearity generated by the price rigidity channel.

Nonlinearity in the benchmark model. Panel (a) of Figure 3 shows the results for the benchmark model. Inflation shows clear nonlinearity. After a large productivity shock (5%), actual inflation reaches 3.9% per annum, while the extrapolated inflation is only 3.4%. In other words, inflation upon impact is amplified by 15% due to the price rigidity channel. As expected, higher inflation helps stabilize markups after large shocks. The aggregate markup falls from 21.1% to 12.1%, whereas linear extrapolation predicts a much lower level of 8.1%.

As I increase the shock size from large (5%) to extreme (10%), nonlinearity becomes even stronger, and markups are even further away from the extrapolated markup. Indeed, the extrapolated markup falls below zero, while it appears counterfactual that the average firm is willing to sell at negative markups in any situation. In this sense, the benchmark model delivers not only more stable but also more realistic markups.

Higher volatility in the benchmark model. The stabilization of markups, however, comes at the expense of the stability of the macroeconomy. Recall that $\xi_{i,t}$ in equation 2.14 is always non-negative, meaning that the Phillips curve can never be flatter than the pre-shock slope. As such, the initial amplification of inflation is not compensated by any faster decline in inflation in the future. This is evident in the impulse response functions (IRFs) of the benchmark model in Figure A4. Similar to Figure 3, I plot the linearly extrapolated IRFs in dotted green lines along with the actual IRFs in black lines. Following either a large shock or a medium shock, actual inflation and extrapolated inflation never cross, and thus the price rigidity channel amplifies not only initial inflation but also cumulative inflation. The same applies to the output gap as well.[27] Higher inflation leads to tighter monetary policy and larger output losses. Consequently, inflation volatility and output volatility are both amplified across all time horizons after negative shocks, leading to unambiguous destabilizing effects on the economy. Finally, the nonlinear nature of the model means that the destabilizing effects increase in the size of the shock, which further reduces the welfare of the economy.

Linearity in the unconstrained model. Contrary to the benchmark model, the unconstrained model shows high linearity. In panel (b) of Figure 3, initial responses of both inflation and the markup change linearly as I increase the shock size. Actual responses are almost completely identical to the extrapolated values. Similarly, all impulse response functions in Figure A5 confirm the linearity.

Other differences. A few other differences between the two models are worth noting. First, note that the benchmark model has a higher steady-state markup than the unconstrained one, even though they have the same elasticity of substitution. In other words, the presence of occasionally binding financial constraints can have a nontrivial effect on markups even in a minimalist model (3% in this case). This is similar to the precautionary pricing channel described in Born and Pfeifer (2021). Firms want to raise prices during negative shocks, and financially constrained firms particularly want to do so because they cannot afford losses in bad times. Yet sticky prices prevent free adjustments to the shock. As such, financially constrained firms would prefer higher steady-state prices as a hedge, so that in bad times they can be closer to the desired prices more easily.

Second, it is useful to compare how borrowing differs in the two models. In Figures A4 and A5, I plot the IRF of debt normalized by steady-state sales. In the benchmark model, debt moderately increases after a small shock. However, as the shock size increases, financial constraints become tighter, and the initial debt response turns from positive to slightly negative. Meanwhile, in the unconstrained model, firms increase borrowing to smooth dividends after shocks, and the size of borrowing is highly linear in the shock size.

4.4 The Role of Monetary and Other Policies

To offset the destabilizing effects caused by the price rigidity channel, one ultimately needs to relax the financial constraints. Whether monetary policy can achieve this goal depends crucially on profit cyclicality with respect to demand shocks.[28] If profits are procyclical enough with

[27] I define the output gap as the deviation from the steady-state output.

[28] Like most three-equation models, the simple model in this section is unable to generate procyclical profits after demand shocks, making it unsuitable for evaluating optimal monetary policy.

respect to demand shocks, accommodative monetary policy can stimulate demand, improve profitability, and relax financial constraints. Yet, loose monetary policy is also inflationary by itself. Therefore, the price rigidity channel complicates monetary policy trade-offs, particularly during large negative shocks.

Many less conventional policies have been explored since COVID, albeit not always inspired by the mechanism discussed in this paper. Energy subsidies had a significant effect on inflation in the Euro Area (Dao et al., 2023). The cost, however, is also nontrivial. For instance, one estimate shows that the French energy tariff shield lowered cumulative inflation by 2.2% at a fiscal cost of 2.2% of GDP between 2022 and 2023. I leave for future research how these alternative policies may interact with the finance-price nexus.

5 Robustness to Alternative Pricing Models

In this section, I analytically show that propositions 1 and 2 do not change in Calvo and menu-cost models.

Calvo pricing. The Calvo case is derived in Section C.1. The optimal reset price is defined in equation 5.1:

$$0 = (1+\xi^*_{i,t})\frac{\partial \text{EBIDTA}_{i,t|P^*_{i,t}}}{\partial P^*_{i,t}} + \text{E}_t\sum_{k=1}^{\infty}\Lambda_{t+1,t+k}\theta^k(1+\xi_{i,t+k})\frac{P_t}{P_{t+k}}\frac{\partial \text{EBIDTA}_{i,t+h|P^*_{i,t}}}{\partial P^*_{i,t}}, \tag{5.1}$$

where $(1-\theta)$ is the probability of resetting the price, $P^*_{i,t}$ is the optimal reset price, $\xi^*_{i,t} = \xi^{div,*}_{i,t} + \xi^{ebc,*}_{i,t}\phi_i$, and $\xi_{i,t+k} = \xi^{div}_{i,t+k} + \xi^{ebc}_{i,t+k}\phi_i$. Mathematically, $\xi^{div,*}_{i,t}$ and $\xi^{ebc,*}_{i,t}$ are the Lagrangian multipliers on the dividend and borrowing constraints when firm i is able to reset the price to $P^*_{i,t}$, whereas $\xi^{div}_{i,t+k}$ and $\xi^{ebc}_{i,t+k}$ are the future Lagrangian multipliers when firm i has not been able to reset its price since $P^*_{i,t}$. Economically, $\xi^*_{i,t}$ is the shadow value of internal cash flows at t when firm i can reset its price, and $\xi_{i,t+k}$ is the shadow value in the future before firm i can reset again.

The limiting case under Calvo pricing is when (i) $\xi^*_{i,t} \to \infty$ and (ii) $\forall h, \frac{\xi^*_{i,t}}{\xi_{i,t+h}} \to \infty$. $\frac{\partial \text{EBIDTA}_{i,t|P^*_{i,t}}}{\partial P^*_{i,t}} = 0$ in the limiting case, which means that the optimal reset price satisfies equation 2.16. As a result, propositions 1 and 2 both remain valid.

Menu-cost models. In order to derive analytical results, I add a quadratic general hazard function to the Calvo model. The probability of changing prices is now a quadratic function of the price gap between the old price and the desired reset price. Importantly, this functional assumption is empirically successful as shown in Gagliardone et al. (2024). Interestingly, the limiting case of this Calvo-plus model is exactly the same as the limiting case of the Calvo model above. The derivation is in Section C.2.

6 Conclusions

In this paper, I find that financial constraints weaken price rigidities both in theory and in the data. My theoretical predictions are robust in different pricing models, namely Rotemberg, Calvo, and menu-cost models. Empirically, financially constrained firms choose higher cost pass-through upfront, particularly during large cost shocks, and revise prices downward as shocks fade. By contrast, financially unconstrained firms choose lower cost pass-through and a smoother trajectory of prices in two years. Financially constrained firms also show almost zero strategic complementarities, suggesting that they are less affected by not only nominal but also real rigidities. The empirical findings are consistent with my theoretical predictions. In a textbook New Keynesian model with financial frictions, this price rigidity channel can create nonlinearity in the slope of the Phillips curve. The model predicts substantial amplification of inflation during supply shocks, and the amplification increases in the size of the shock. The combination of weakened rigidities and large shocks makes the economy more volatile and reduces welfare.

References

Abraham, F., Y. Bormans, J. Konings, and W. Roeger (Sept. 2024). "Price-Cost Margins, Fixed Costs and Excess Profits". *The Economic Journal* 134.663, pp. 2655–2684. ISSN: 0013-0133.

Alexander, P., L. Han, O. Kryvtsov, and B. Tomlin (2024). "Markups and Inflation in Oligopolistic Markets: Evidence from Wholesale Price Data".

Almeida, H. (2012). "Corporate Debt Maturity and the Real Effects of the 2007 Credit Crisis". *Critical Finance Review* 1.1. ISSN: 21645744.

Amiti, M., O. Itskhoki, and J. Konings (2019). "International Shocks, Variable Markups, and Domestic Prices". *Review of Economic Studies* 86.6. ISSN: 1467937X.

Atkeson, A. and A. Burstein (2008). "Pricing-to-market, trade costs, and international relative prices". *American Economic Review* 98.5. ISSN: 00028282.

Auclert, A., B. Bardóczy, M. Rognlie, and L. Straub (2021). "Using the Sequence-Space Jacobian to Solve and Estimate Heterogeneous-Agent Models". *Econometrica* 89.5. ISSN: 0012-9682.

Balduzzi, P., E. Brancati, M. Brianti, and F. Schiantarelli (2024). "Credit constraints and firms' decisions: Lessons from the COVID-19 outbreak". *Journal of Monetary Economics* 142. ISSN: 03043932.

Ball, L., D. Leigh, and P. Mishra (Oct. 2022). *Understanding U.S. Inflation During the COVID Era*. Tech. rep. Cambridge, MA: National Bureau of Economic Research.

Balleer, A., N. Hristov, and D. Menno (2017). "Menu Costs, the Price Gap Distribution and Monetary Non-Neutrality: The Role of Financial Constraints".

Benigno, P. and G. B. Eggertsson (2023). "It's Baaack: The Surge in Inflation in the 2020s and the Return of the Non-Linear Phillips Curve".

Berardi, N. (2025). *Raising Prices While Struggling: Firms' Financial Constraints and Price Setting*.

Bhattarai, S., G. B. Eggertsson, and R. Schoenle (2018). "Is increased price flexibility stabilizing? Redux". *Journal of Monetary Economics* 100. ISSN: 03043932.

Blanco, A., C. Boar, C. Jones, and V. Midrigan (2024). “Nonlinear Inflation Dynamics in Menu Cost Economies”. *Finance and Economics Discussion Series* 2024-005. ISSN: 1936-2854.

Born, B. and J. Pfeifer (2021). “Uncertainty-driven business cycles: Assessing the markup channel”. *Quantitative Economics* 12.2. ISSN: 1759-7323.

Caglio, C., R. M. Darst, and Kalemli-Özcan (Apr. 2021). *Collateral Heterogeneity and Monetary Policy Transmission: Evidence from Loans to SMEs and Large Firms.* Tech. rep. Cambridge, MA: National Bureau of Economic Research.

Capelle, D. and Y. Liu (Dec. 2023). “Optimal Taxation of Inflation”. *IMF Working Papers* 2023.254, p. 1. ISSN: 1018-5941.

Chevalier, J. A. and D. S. Scharfstein (1996). “Capital-Market Imperfections and Countercyclical Markups: Theory and Evidence”. *American Economic Review* 86.4. ISSN: 00028282.

Christiano, L. J., M. S. Eichenbaum, and M. Trabandt (2015). “Understanding the great recession”. *American Economic Journal: Macroeconomics* 7.1. ISSN: 19457715.

Crouzet, N. and N. R. Mehrotra (2020). “Small and Large Firms over the Business Cycle”. *American Economic Review* 110.11. ISSN: 19447981.

Dao, M., A. Dizioli, C. Jackson, P.-O. Gourinchas, and D. Leigh (2023). “Unconventional Fiscal Policy in Times of High Inflation”. *IMF Working Papers* 2023.178. ISSN: 1018-5941.

De Loecker, J., P. K. Goldberg, A. K. Khandelwal, and N. Pavcnik (2016). “Prices, Markups, and Trade Reform”. *Econometrica* 84.2. ISSN: 0012-9682.

Forbes, K. J., J. E. Gagnon, and C. G. Collins (2022). “Low Inflation Bends the Phillips Curve around the World”. *Economia* 45.89. ISSN: 0254-4415.

Gagliardone, L., M. Gertler, S. Lenzu, and J. Tielens (June 2023). *Anatomy of the Phillips Curve: Micro Evidence and Macro Implications.* Tech. rep. Cambridge, MA: National Bureau of Economic Research.

— (2024). “Micro and Macro Cost-Price Dynamics across Inflation Regimes”.

Gilchrist, S., R. Schoenle, J. Sim, and E. Zakrajšek (2017). “Inflation dynamics during the financial crisis”. *American Economic Review* 107.3. ISSN: 00028282.

Goldberg, P. K., A. K. Khandelwal, N. Pavcnik, and P. Topalova (2010a). “Multiproduct firms and product turnover in the developing world: Evidence from India”. *Review of Economics and Statistics* 92.4. ISSN: 00346535.

Goldberg, P. K., A. K. Khandelwal, N. Pavcnik, and P. Topalova (2010b). “Imported intermediate inputs and domestic product growth: Evidence from India”. *Quarterly Journal of Economics* 125.4. ISSN: 00335533.

Hadlock, C. J. and J. R. Pierce (2010). “New evidence on measuring financial constraints: Moving beyond the KZ index”. *Review of Financial Studies* 23.5. ISSN: 08939454.

Harding, M., J. Lindé, and M. Trabandt (2023). “Understanding post-COVID inflation dynamics”. *Journal of Monetary Economics* 140. ISSN: 03043932.

Holden, T. (2024). *Rationing under Sticky Prices.*

Khan, A. and J. K. Thomas (2013). “Credit shocks and aggregate fluctuations in an economy with production heterogeneity”. *Journal of Political Economy* 121.6. ISSN: 00223808.

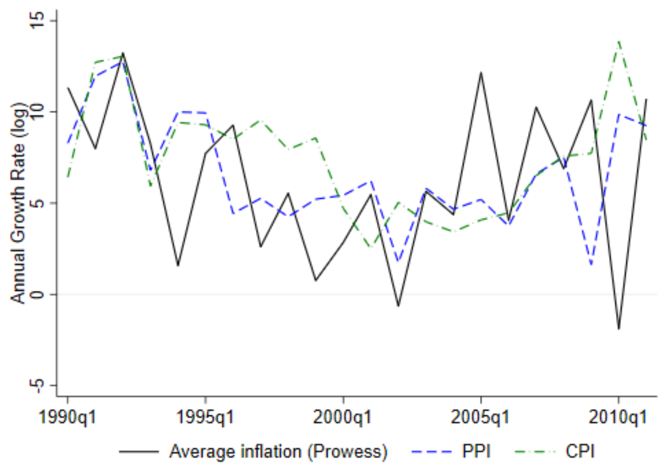
Kim, R. (2021). “The Effect of the Credit Crunch on Output Price Dynamics: The Corporate Inventory and Liquidity Management Channel”. *Quarterly Journal of Economics* 136.1. ISSN: 15314650.

Lenzu, S., D. A. Rivers, J. Tielens, and S. Hu (2024). “Financial Shocks and Productivity: Pricing Response and the TFPR-TFPQ Bifurcation”. *SSRN Electronic Journal.* ISSN: 1556-5068.

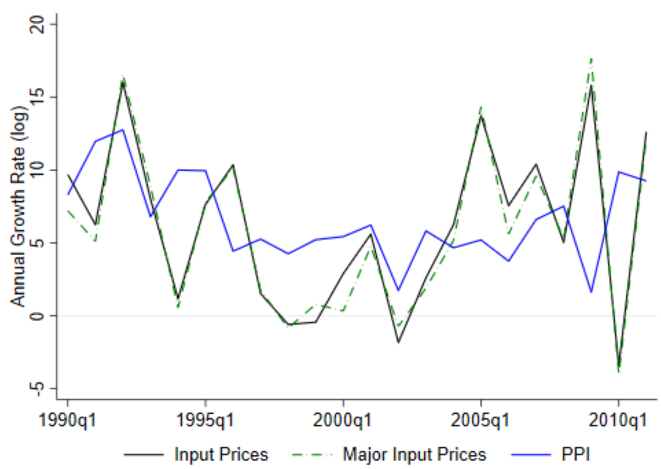
Montero, J. M. and A. Urtasun (Jan. 2021). "Markup dynamics and financial frictions: The Spanish case". *International Review of Economics & Finance* 71, pp. 316–341. ISSN: 10590560.
Ottonello, P. and T. Winberry (2020). "Financial Heterogeneity and the Investment Channel of Monetary Policy". *Econometrica* 88.6. ISSN: 0012-9682.
Ravn, M., S. Schmitt-Grohé, and M. Uribe (2006). "Deep Habits". *Review of Economic Studies* 73.1. ISSN: 00346527.
Renkin, T. and G. Züllig (Apr. 2024). "Credit Supply Shocks and Prices: Evidence from Danish Firms". *American Economic Journal: Macroeconomics* 16.2, pp. 1–28. ISSN: 1945-7707.
Rotemberg, J. J. (1982). "Sticky Prices in the United States". *Journal of Political Economy* 90.6. ISSN: 0022-3808.
Schmitt-Grohé, S. and M. Uribe (Dec. 2022). *Heterogeneous Downward Nominal Wage Rigidity: Foundations of a Nonlinear Phillips Curve*. Tech. rep. Cambridge, MA: National Bureau of Economic Research.
Strasser, G. (2013). "Exchange rate pass-through and credit constraints". *Journal of Monetary Economics* 60.1. ISSN: 03043932.
Wang, O. and I. Werning (2022). "Dynamic Oligopoly and Price Stickiness". *American Economic Review* 112.8. ISSN: 19447981.

Appendix

A Additional Tables and Figures



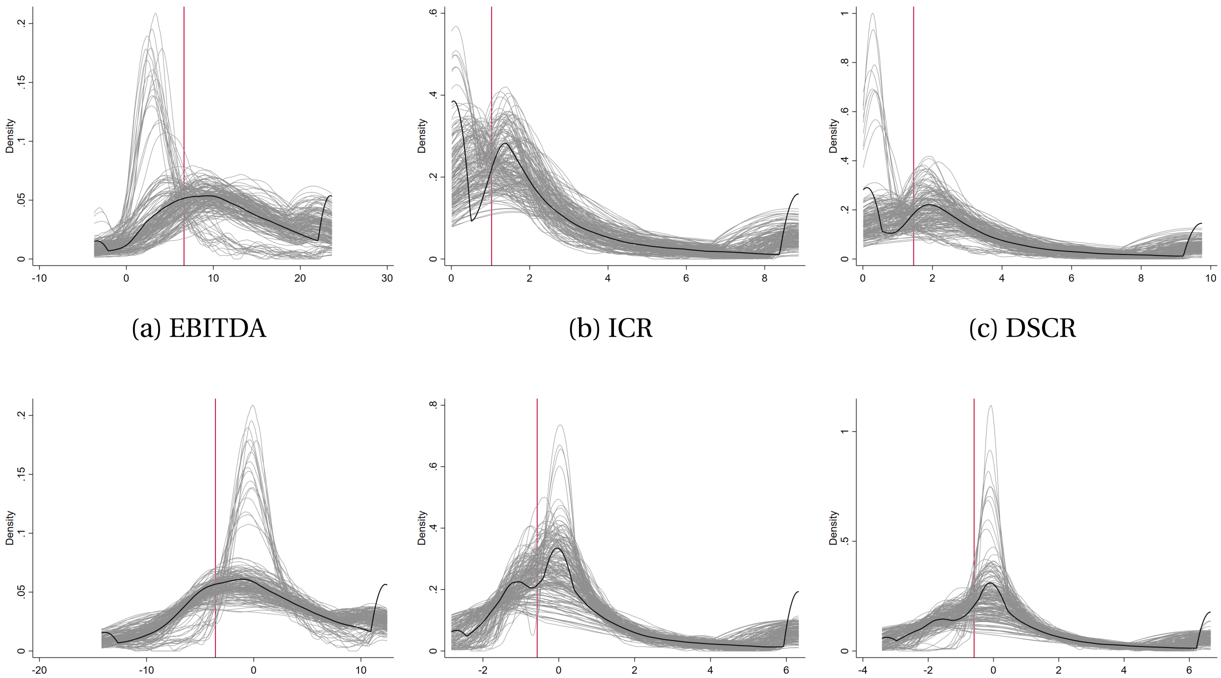
(a) Output Prices



(b) Input Prices

Notes: Average inflation in Prowess is defined as the average price changes weighted by sales among manufacturing firms. PPI, also called the Wholesale Price Index (WPI), includes all industries (FRED series: INDWPIATT01GPM). CPI includes all items (FRED series: INDCPIALLMINMEI). Growth rates are from March to March, corresponding to the timing in Prowess.

Figure A1: Aggregate Prices in India

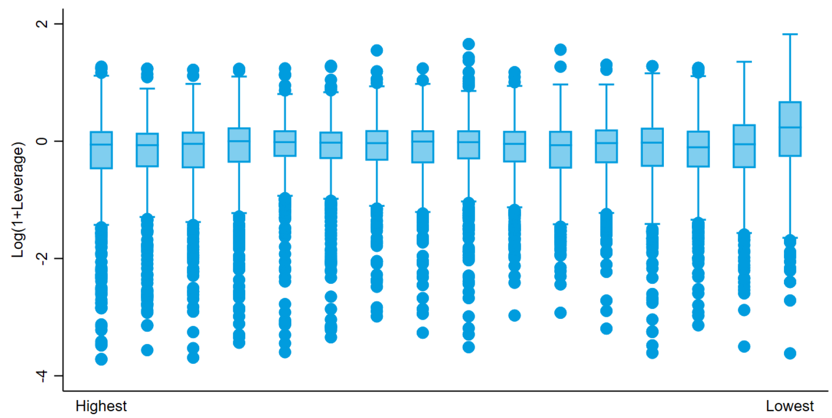


(a) EBITDA (b) ICR (c) DSCR

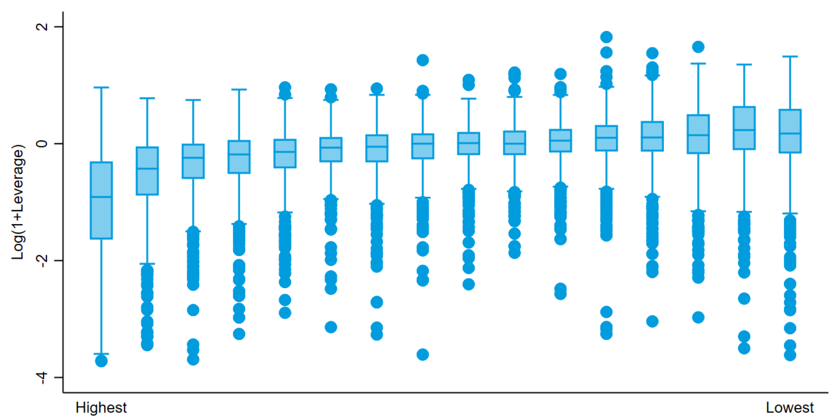
(d) EBITDA (adj.) (e) ICR (adj.) (f) DSCR (adj.)

Notes: The upper three panels show the kernal density functions of the EBITDA, ICR, and DSCR, each winsorized at the 2.5th and 90th percentiles. The black lines are the density functions of all firms in the 2-digit sector-year pairs that ever appear in the regression sample from column (1) of Table 2. The gray lines are density functions estimated for each 2-digit sector in each year. The vertical lines show the 25th percentile within the regression sample from column (1) of Table 2. In the lower three panels, I remove the sector-year medians from the variables.

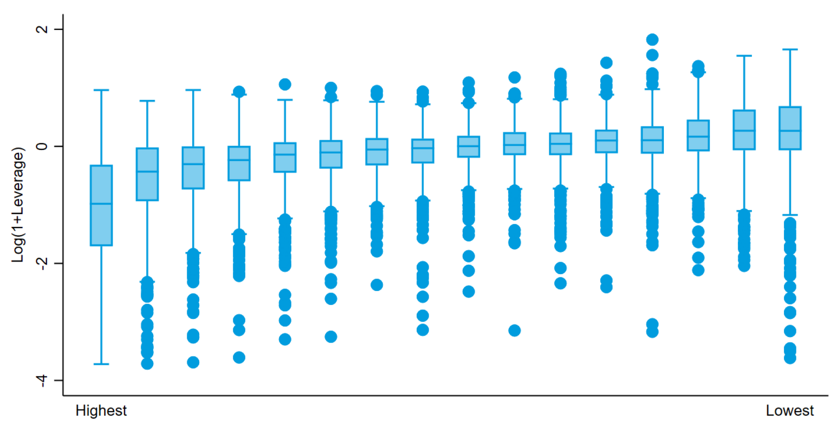
Figure A2: Distributions of Financial Variables



(a) EBITDA



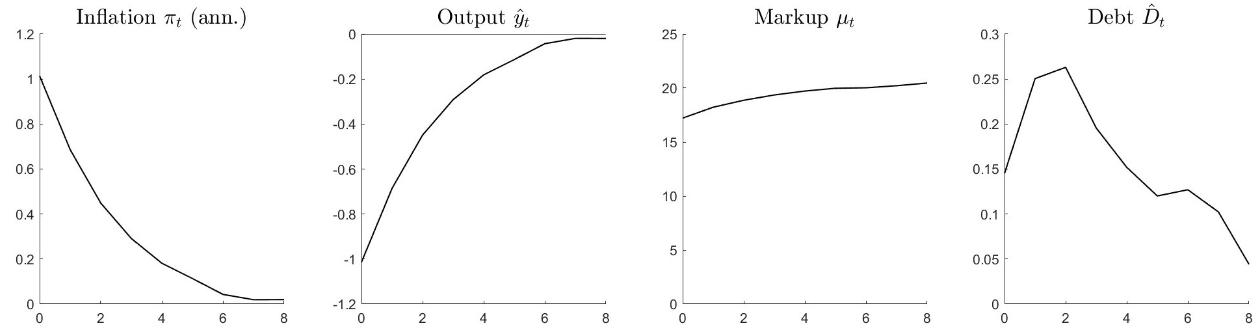
(b) ICR



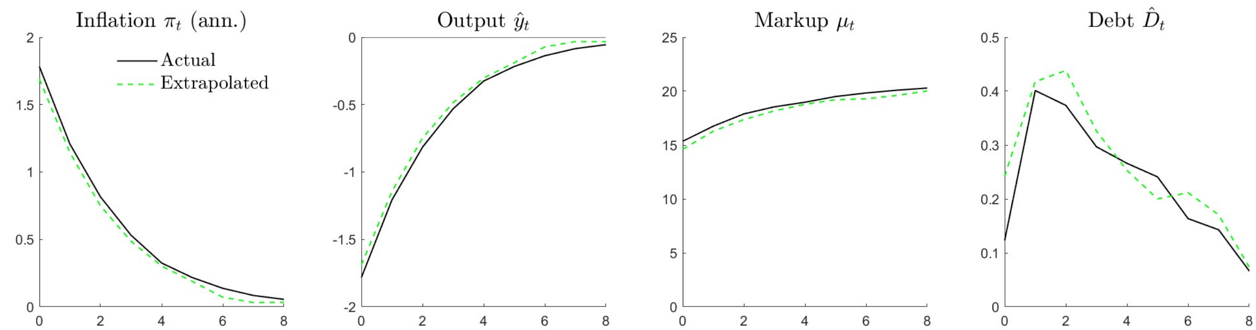
(c) DSCR

Notes: xxx

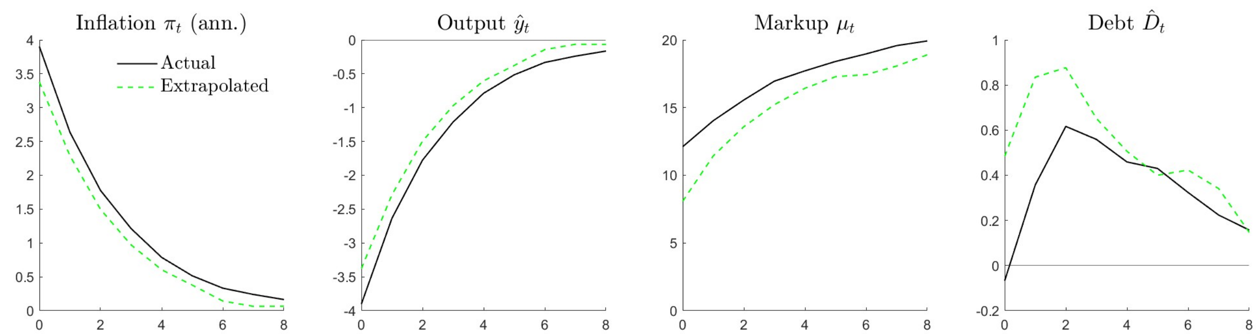
Figure A3: Leverage Distribution



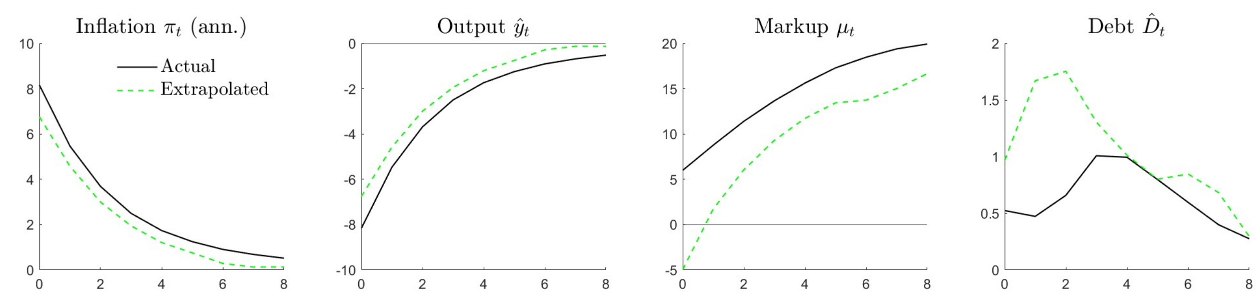
(a) Small Productivity Shock (1.5%)



(b) Medium Productivity Shock (2.5%)



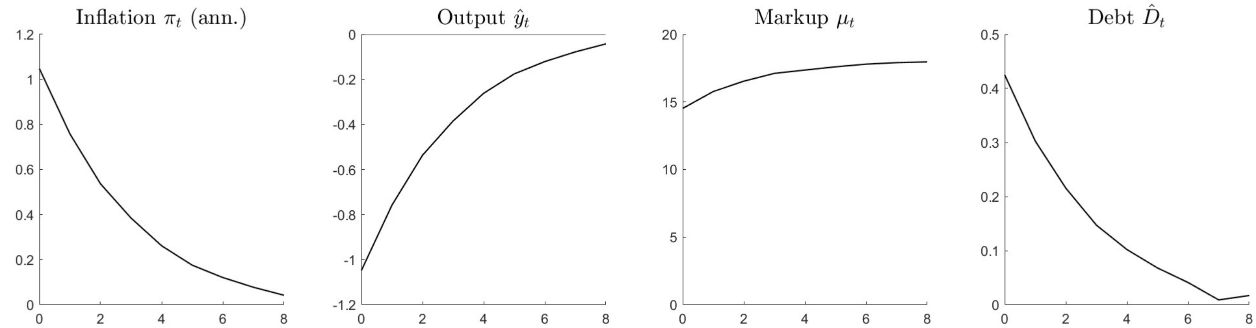
(c) Large Productivity Shock (5%)



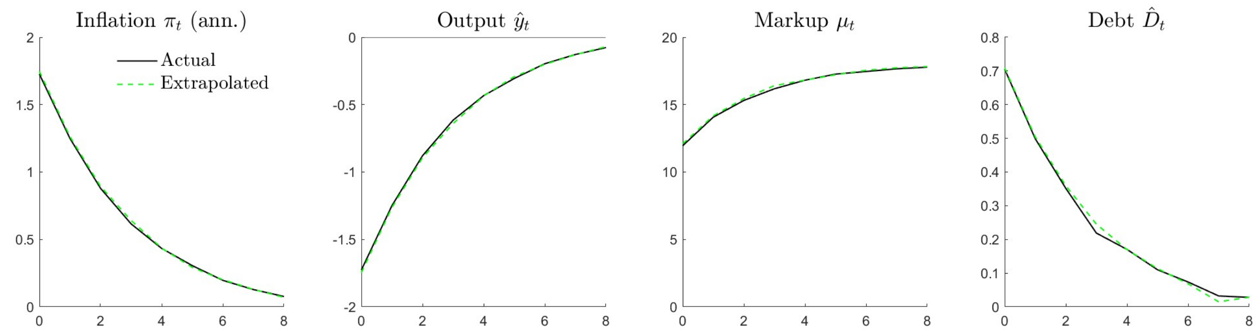
(d) Extreme Productivity Shock (10%)

Notes: All variables are in percentage points. For inflation, output, and debt I show the deviation from the steady state value. Debt $\hat{D}_t$ is normalized by steady state sales. For markup, I show the level instead of the deviation.

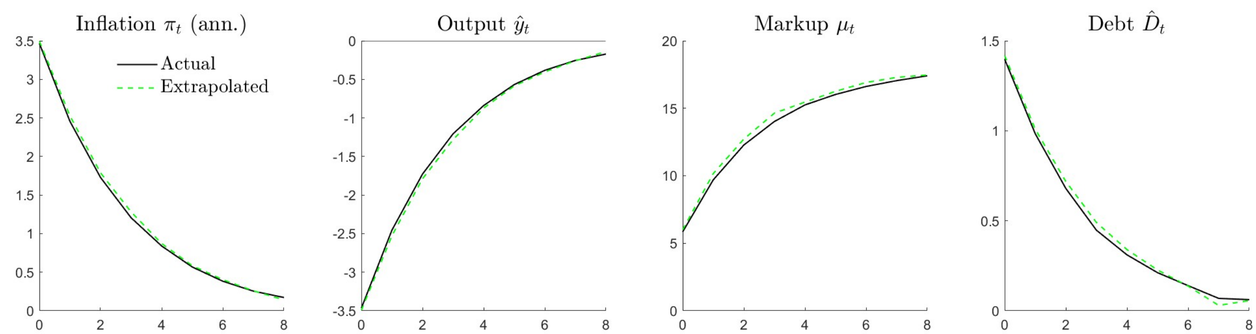
Figure A4: Impulse Response Functions of the Benchmark Model



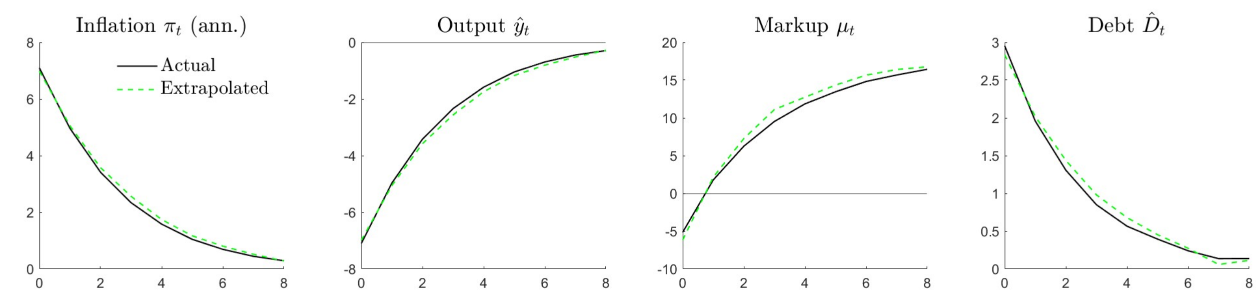
(a) Small Productivity Shock (-1.5%)



(b) Medium Productivity Shock (-2.5%)



(c) Large Productivity Shock (-5%)



(d) Large Productivity Shock (-5%)

Notes: All variables are in percentage points. For inflation, output, and debt I show the deviation from the steady state value. Debt $\hat{D}_t$ is normalized by steady state sales. For markup, I show the level instead of the deviation.

Figure A5: Impulse Response Functions of the Unconstrained Model

	High ICR (N = 7,486)				Low ICR (N = 2,252)			
	P10	Median	P90	S.D.	P10	Median	P90	S.D.
A. Firm Size (in constant 1990 Rupees)								
Sales (in log)	4.23	5.75	7.08	1.09	3.81	5.25	6.81	1.15
Assets (in log)	4.10	5.54	7.06	1.11	3.67	5.11	6.82	1.16
B. Profit Margins and Financial Ratios								
COGS margin	13.8	26.8	41.5	10.8	9.1	23.7	38.6	11.5
EBITDA margin	4.1	11.3	21.0	7.2	-1.7	8.3	19.4	9.1
Current liability-to-asset ratio	6.4	16.8	36.1	12.4	9.5	23.9	55.3	19.8
Leverage ratio	12.6	36.7	59.3	18.2	18.3	45.4	100	27.3
Interest coverage ratio	0.4	2.1	10.2	12.8	0.0	1.0	3.8	8.4
Debt service ratio	0.7	2.8	10.7	12.6	-0.4	1.5	4.9	9.5
Current ratio	0.8	1.3	2.0	0.6	0.5	1.0	1.8	0.6
C. Price Changes								
$\Delta p_{i,t}$	-11.2	3.0	19.5	14.3	-10.6	3.7	22.7	15.3
$\Delta mc_{i,t}^{\text{nom.}}$	-11.6	4.0	21.5	15.0	-13.5	4.3	24.3	16.8
$\Delta p_{-i,t}$	-5.0	2.7	13.3	8.5	-4.5	3.2	14.1	8.4
$(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t}$	-7.3	1.6	13.5	9.7	-6.4	2.1	14.8	9.6
$(x^{\text{mj}}\Delta\rho^{\text{mj}})_{-i,t}$	-3.0	1.8	8.6	5.4	-2.7	2.2	9.7	5.7
D. Other Characteristics								
Share of imported raw materials	0.0	0.2	42.1	20.6	0.0	0.0	38.5	19.3
Share of export revenues	0.0	2.9	37.2	17	0.0	1.0	30.3	16.6
Industry scope (6-digit industries)	1.0	1.0	3.0	0.82	1.0	1.0	3.0	0.76
Market share (6-digit industries)	0.1	0.7	4.3	3.0	0.1	0.4	2.9	2.0

Notes: See Table 1 for the definition of variables.

Table A1: Summary Statistics by ICR

	High ICR (N = 7,406)				Low ICR (N = 2,332)			
	P10	Median	P90	S.D.	P10	Median	P90	S.D.
A. Firm Size (in constant 1990 Rupees)								
Sales (in log)	4.21	5.73	7.07	1.09	3.84	5.34	6.90	1.15
Assets (in log)	4.07	5.53	7.05	1.12	3.76	5.15	6.87	1.15
B. Profit Margins and Financial Ratios								
COGS margin	13.8	26.7	41.4	10.8	9.0	24.0	39.0	11.6
EBITDA margin	4.1	11.4	21.2	7.2	-1.2	8.3	18.9	8.8
Current liability-to-asset ratio	6.4	16.7	35.9	12.3	9.6	24.2	54.8	19.6
Leverage ratio	12.0	36.1	58.7	18.1	20.9	47.0	100.0	26.3
Interest coverage ratio	0.4	2.1	10.3	13	0.0	1.0	3.2	7.9
Debt service ratio	0.8	2.8	11.1	12.9	-0.3	1.5	4	8.2
Current ratio	0.9	1.3	2.1	0.6	0.5	1.0	1.7	0.6
C. Price Changes								
$\Delta p_{i,t}$	-11.3	3.0	19.3	14.3	-10.4	3.8	23.3	15.1
$\Delta mc_{i,t}^{\text{nom.}}$	-11.7	3.9	21.4	15.0	-13.2	4.6	24.6	16.6
$\Delta p_{-i,t}$	-5.0	2.6	13.2	8.4	-4.4	3.5	14.3	8.5
$(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t}$	-7.3	1.6	13.3	9.7	-6.2	2.2	15.2	9.6
$(x^{\text{mj}}\Delta\rho^{\text{mj}})_{-i,t}$	-3.0	1.8	8.5	5.4	-2.6	2.3	9.8	5.8
D. Other Characteristics								
Share of imported raw materials	0.0	0.1	42.1	20.5	0.0	0.0	38.2	19.5
Share of export revenues	0.0	2.9	37.1	16.9	0.0	1.1	31.5	16.8
Industry scope (6-digit industries)	1.0	1.0	3.0	0.82	1.0	1.0	3.0	0.77
Market share (6-digit industries)	0.1	0.7	4.3	3.0	0.1	0.4	3.0	2.1

Notes: See Table 1 for the definition of variables.

Table A2: Summary Statistics by DSCR

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable: $\Delta p_{i,t}$		Spec A			Spec B	
$\Delta mc_{i,t}$ ($\hat{\beta}_0$)	0.64^{***}	0.64^{***}	0.64^{***}	0.63^{***}	0.70^{***}	0.68^{***}
	(0.05)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)
Tight × $\Delta mc_{i,t}$ ($\hat{\beta}_1$)	0.23^{***}	0.21^{**}	0.19^{**}	0.21^{**}	0.12^{**}	0.14^{**}
	(0.08)	(0.09)	(0.08)	(0.08)	(0.06)	(0.06)
$\Delta p_{-i,t}$ ($\hat{\gamma}_0$)	0.35^{***}	0.35^{***}	0.27^{***}	0.33^{**}		
	(0.08)	(0.08)	(0.08)	(0.13)		
Tight × $\Delta p_{-i,t}$ ($\hat{\gamma}_1$)	-0.27^{***}	-0.26^{**}	-0.23^{**}	-0.25^{**}		
	(0.10)	(0.11)	(0.10)	(0.10)		
Tight	0.02^{***}	0.02^{***}	0.01^{***}	0.01^{***}	0.01^{*}	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y				
Sector FE	Y					
Industry FE		Y				
Sector-Year FE			Y		Y	
Industry-Year FE				Y		Y
R^2	0.724	0.726	0.686	0.669	0.688	0.677
N	9,738	9,065	9,738	9,065	9,738	9,065
Firms	826	797	826	797	826	797
Two-digit Sectors	9		9		9	
Four-digit Industries		25		25		25
Weak IV F-test						
Cragg-Donald	64.65	59.32	65.63	58.30	244.00	222.98
Kleibergen-Paap	7.85	6.46	7.00	7.70	9.89	11.35
Hansen J-test χ^2	0.731	1.957	2.139	2.755	0.930	0.446
p value	0.947	0.744	0.710	0.600	0.628	0.800
Financial Amplification						
$\hat{\beta}_0 + \hat{\beta}_1$	0.87***	0.85***	0.83***	0.84***	0.82***	0.81***
$\hat{\gamma}_0 + \hat{\gamma}_1$	0.09	0.09	0.04	0.08		

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

Notes: The table replicates Table 2 but replaces the dummy variable with the low-ICR dummy. The low-ICR dummy is defined using the 25th percentile of the regression sample.

Table A3: Effects of Financial Constraints on Current Prices - ICR

Dep. variable: $\Delta p_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)
		Spec A			Spec B	
$\Delta mc_{i,t}$ ($\hat{\beta}_0$)	0.64***	0.64***	0.64***	0.62***	0.70***	0.67***
	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)
Tight × $\Delta mc_{i,t}$ ($\hat{\beta}_1$)	0.19**	0.18*	0.17**	0.22**	0.11*	0.13**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.06)	(0.06)
$\Delta p_{-i,t}$ ($\hat{\gamma}_0$)	0.35***	0.35***	0.27***	0.34***		
	(0.08)	(0.08)	(0.08)	(0.13)		
Tight × $\Delta p_{-i,t}$ ($\hat{\gamma}_1$)	-0.23**	-0.23**	-0.22**	-0.28***		
	(0.10)	(0.11)	(0.10)	(0.11)		
Tight	0.02***	0.02***	0.02***	0.01***	0.01**	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y				
Sector FE	Y					
Industry FE		Y				
Sector-Year FE			Y		Y	
Industry-Year FE				Y		Y
R^2	0.724	0.725	0.685	0.665	0.687	0.675
N	9,738	9,065	9,738	9,065	9,738	9,065
Firms	826	797	826	797	826	797
Two-digit Sectors	9		9		9	
Four-digit Industries		25		25		25
Weak IV F-test						
Cragg-Donald	64.65	59.32	65.63	58.30	244.00	222.98
Kleibergen-Paap	11.02	13.91	13.38	9.74	24.37	27.45
Hansen J-test χ^2	1.823	2.346	2.530	3.590	0.937	0.619
p value	0.768	0.672	0.639	0.464	0.626	0.734
Financial Amplification						
$\hat{\beta}_0 + \hat{\beta}_1$	0.83***	0.82***	0.81***	0.84***	0.81***	0.80***
$\hat{\gamma}_0 + \hat{\gamma}_1$	0.12	0.13	0.05	0.06		

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

Notes: The table replicates Table 2 but replaces the dummy variable with the low-DSCR dummy. The low-DSCR dummy is defined using the 25th percentile of the regression sample.

Table A4: Effects of Financial Constraints on Current Prices - DSCR

Dep. variable: $\Delta p_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	x = EBITDA				x = ICR				x = DSCR			
Direct Pass-through												
$\Delta mc_{i,t}$ ($\hat{\beta}_1^*$)	0.86***	0.89***	0.88***	0.83***	0.84***	0.86***	0.83***	0.83***	0.81***	0.85***	0.81***	0.81***
	(0.07)	(0.07)	(0.05)	(0.05)	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.08)	(0.06)	(0.06)
$x \in (25^{\text{th}}, 50^{\text{th}}] \times \Delta mc_{i,t}$ ($\hat{\beta}_2^*$)	-0.13	-0.19**	-0.09	-0.05	-0.27**	-0.28**	-0.20**	-0.20**	-0.31**	-0.30**	-0.19**	-0.18*
	(0.09)	(0.09)	(0.06)	(0.05)	(0.11)	(0.11)	(0.09)	(0.08)	(0.14)	(0.13)	(0.10)	(0.09)
$x \in (50^{\text{th}}, 75^{\text{th}}] \times \Delta mc_{i,t}$ ($\hat{\beta}_3^*$)	-0.24**	-0.28***	-0.22***	-0.19***	-0.23**	-0.27***	-0.14*	-0.18**	-0.19**	-0.25**	-0.13**	-0.15**
	(0.10)	(0.11)	(0.06)	(0.06)	(0.10)	(0.10)	(0.08)	(0.08)	(0.09)	(0.10)	(0.07)	(0.07)
Highest x ($\geq 75^{\text{th}}$) $\times \Delta mc_{i,t}$ ($\hat{\beta}_4^*$)	-0.25**	-0.33***	-0.20***	-0.18***	-0.10	-0.14	-0.08	-0.12*	-0.06	-0.14	-0.06	-0.10
	(0.10)	(0.11)	(0.07)	(0.07)	(0.10)	(0.11)	(0.07)	(0.07)	(0.11)	(0.12)	(0.08)	(0.08)
Strategic Complementarity												
$\Delta p_{-i,t}$ ($\hat{\gamma}_1^*$)	0.04	0.08			0.03	0.03			0.04	0.06		
	(0.08)	(0.12)			(0.09)	(0.13)			(0.09)	(0.13)		
$x \in (25^{\text{th}}, 50^{\text{th}}] \times \Delta p_{-i,t}$ ($\hat{\gamma}_2^*$)	0.15	0.21**			0.29**	0.31**			0.39**	0.39***		
	(0.11)	(0.10)			(0.12)	(0.13)			(0.16)	(0.15)		
$x \in (50^{\text{th}}, 75^{\text{th}}] \times \Delta p_{-i,t}$ ($\hat{\gamma}_3^*$)	0.23*	0.27*			0.30**	0.36***			0.23*	0.33**		
	(0.14)	(0.14)			(0.12)	(0.13)			(0.12)	(0.13)		
Highest x ($\geq 75^{\text{th}}$) $\times \Delta p_{-i,t}$ ($\hat{\gamma}_4^*$)	0.32**	0.42***			0.11	0.17			0.08	0.18		
	(0.15)	(0.15)			(0.15)	(0.16)			(0.16)	(0.15)		
Others												
$x \in (25^{\text{th}}, 50^{\text{th}}]$	-0.01***	-0.01***	-0.01**	-0.01***	-0.01***	-0.01**	-0.00	0.00	-0.01**	-0.01*	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
$x \in (50^{\text{th}}, 75^{\text{th}}]$	-0.02***	-0.02***	-0.01***	-0.01***	-0.02***	-0.02***	-0.01	-0.01	-0.02***	-0.02***	-0.01*	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Highest x ($\geq 75^{\text{th}}$)	-0.03***	-0.04***	-0.03***	-0.03***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Year FE	Y		Y		Y		Y		Y		Y	
Industry-Year FE		Y		Y		Y		Y		Y		Y
R^2	0.693	0.672	0.694	0.684	0.684	0.668	0.687	0.676	0.677	0.660	0.684	0.674
N	9,738	9,065	9,738	9,065	9,738	9,065	9,738	9,065	9,738	9,065	9,738	9,065
Firms	826	797	826	797	826	797	826	797	826	797	826	797
Two-digit Sectors	9		9		9		9		9		9	
Four-digit Industries		25		25		25		25		25		25
Weak IV F-test												
Cragg-Donald	23.92	27.28	98.23	96.07	27.92	28.91	84.41	89.85	18.53	23.13	64.89	73.77
Kleibergen-Paap	3.63	4.73	7.29	7.15	1.70	6.88	4.09	5.62	2.33	1.66	3.24	3.13
Hansen J-test χ^2	14.425	11.669	11.321	5.724	8.577	13.052	1.739	2.614	6.069	5.884	0.874	1.354
p value	0.071	0.167	0.023	0.221	0.379	0.110	0.784	0.624	0.640	0.660	0.928	0.852
Between Less Constrained Firms												
$\hat{\beta}_4^* - \hat{\beta}_3^*$	-0.00	-0.05	0.02	0.01	0.13	0.13	0.06	0.06	0.14	0.11	0.08	0.05
$\hat{\gamma}_4^* - \hat{\gamma}_3^*$	0.09	0.15			-0.19	-0.19			-0.15	-0.15		

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

Notes: The specifications are extended from columns (3)-(6) in Table 2. All elements except for the categorical variable are unchanged.

Table A5: Results Using Non-binary Interactions

Dep. variable: $\Delta p_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	x = EBITDA				x = ICR				x = DSCR			
Tight × Large Increase × $\Delta mc_{i,t}$ ($\hat{\beta}^{\text{T, L}}$)	0.96***	1.03***	0.96***	1.06***	0.95***	1.01***	0.96***	1.05***	0.88***	0.90***	0.91***	1.00***
	(0.09)	(0.15)	(0.10)	(0.13)	(0.15)	(0.15)	(0.15)	(0.17)	(0.14)	(0.14)	(0.15)	(0.17)
Not Tight × Large Increase × $\Delta mc_{i,t}$ ($\hat{\beta}^{\text{NT, L}}$)	0.68***	0.63***	0.67***	0.63***	0.66***	0.61***	0.66***	0.63***	0.67***	0.62***	0.66***	0.62***
	(0.09)	(0.10)	(0.08)	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)
Tight × Not Large × $\Delta mc_{i,t}$ ($\hat{\beta}^{\text{T, NL}}$)	0.81***	0.79***	0.81***	0.79***	0.68***	0.67***	0.56***	0.56***	0.71***	0.71***	0.64***	0.67***
	(0.09)	(0.10)	(0.08)	(0.10)	(0.14)	(0.15)	(0.13)	(0.14)	(0.13)	(0.14)	(0.12)	(0.12)
Not Tight × Not Large × $\Delta mc_{i,t}$ ($\hat{\beta}^{\text{NT, NL}}$)	0.59***	0.61***	0.55***	0.51***	0.64***	0.65***	0.63***	0.59***	0.62***	0.63***	0.61***	0.56***
	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)
Tight × Large Increase × $\Delta p_{-i,t}$ ($\hat{\gamma}^{\text{T, L}}$)	0.06	-0.03	-0.01	-0.03	0.06	0.01	0.01	-0.04	0.15	0.15	0.07	0.00
	(0.12)	(0.17)	(0.12)	(0.17)	(0.15)	(0.15)	(0.15)	(0.17)	(0.13)	(0.14)	(0.13)	(0.18)
Not Tight × Large Increase × $\Delta p_{-i,t}$ ($\hat{\gamma}^{\text{NT, L}}$)	0.36***	0.42***	0.32***	0.42**	0.39***	0.45***	0.32***	0.40***	0.38***	0.44***	0.32***	0.40***
	(0.11)	(0.12)	(0.11)	(0.16)	(0.11)	(0.12)	(0.11)	(0.15)	(0.12)	(0.12)	(0.11)	(0.14)
Tight × Not Large × $\Delta p_{-i,t}$ ($\hat{\gamma}^{\text{T, NL}}$)	0.13	0.14	0.07	0.09	0.20	0.20	0.22	0.24	0.15	0.13	0.11	0.10
	(0.10)	(0.10)	(0.09)	(0.14)	(0.13)	(0.14)	(0.13)	(0.18)	(0.13)	(0.14)	(0.13)	(0.16)
Not Tight × Not Large × $\Delta p_{-i,t}$ ($\hat{\gamma}^{\text{NT, NL}}$)	0.34***	0.31***	0.30**	0.36**	0.30**	0.28**	0.22*	0.26*	0.32***	0.31***	0.23**	0.29*
	(0.12)	(0.11)	(0.12)	(0.15)	(0.12)	(0.11)	(0.11)	(0.14)	(0.12)	(0.11)	(0.12)	(0.15)
Tight	0.02***	0.02***	0.02***	0.02***	0.01***	0.02***	0.01**	0.01***	0.01***	0.02***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Large Increase	-0.00	-0.00	-0.01	-0.01	-0.01	-0.00	-0.01	-0.01	-0.01	-0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tight × Large Increase	-0.00	-0.01	-0.00	-0.01	0.00	-0.01	0.00	-0.01	-0.00	-0.01	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y			Y	Y			Y	Y		
Sector FE	Y				Y				Y			
Industry FE		Y				Y				Y		
Sector-Year FE			Y				Y				Y	
Industry-Year FE				Y				Y				Y
R^2	0.724	0.725	0.672	0.643	0.725	0.721	0.678	0.649	0.724	0.722	0.680	0.646
Weak IV F-test												
Cragg-Donald	13.61	14.32	15.12	17.37	15.12	15.06	17.69	18.06	15.82	16.00	17.70	18.76
Kleibergen-Paap	3.16	4.63	3.91	5.03	1.47	1.76	2.01	2.31	4.32	4.80	4.60	5.15
Hansen J-test χ^2	8.183	9.566	11.746	10.872	8.656	10.380	11.109	12.032	7.982	10.980	9.546	12.126
p value	0.416	0.297	0.163	0.209	0.372	0.239	0.196	0.150	0.435	0.203	0.298	0.146
Financial Amplification												
$\hat{\beta}^{\text{T, L}} - \hat{\beta}^{\text{NT, L}}$	0.27***	0.40***	0.29***	0.43***	0.29*	0.40**	0.30*	0.42**	0.21	0.28*	0.24	0.38**
$\hat{\beta}^{\text{T, NL}} - \hat{\beta}^{\text{NT, NL}}$	0.22	0.17	0.26*	0.27**	0.04	0.02	-0.07	-0.03	0.09	0.09	0.04	0.11
$(\hat{\beta}^{\text{T, L}} - \hat{\beta}^{\text{NT, L}}) - (\hat{\beta}^{\text{T, NL}} - \hat{\beta}^{\text{NT, NL}})$	0.05	0.23	0.03	0.15	0.25	0.38*	0.37*	0.45**	0.12	0.19	0.21	0.26
$\hat{\gamma}^{\text{T, L}} - \hat{\gamma}^{\text{NT, L}}$	-0.30***	-0.45**	-0.33***	-0.45***	-0.33*	-0.44**	-0.32*	-0.43**	-0.23	-0.29*	-0.25	-0.40**
$\hat{\gamma}^{\text{T, NL}} - \hat{\gamma}^{\text{NT, NL}}$	-0.22	-0.17	-0.23	-0.27*	-0.10	-0.08	-0.00	-0.02	-0.17	-0.18	-0.12	-0.19
$(\hat{\gamma}^{\text{T, L}} - \hat{\gamma}^{\text{NT, L}}) - (\hat{\gamma}^{\text{T, NL}} - \hat{\gamma}^{\text{NT, NL}})$	-0.08	-0.28	-0.09	-0.19	-0.23	-0.35*	-0.32	-0.41*	-0.06	-0.11	-0.13	-0.21

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

Notes: Large cost increases refer to firm-years where $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t}$ exceeds its 70th percentile (or 5.3% in nominal terms). The specifications are extended from columns (1)-(4) in Table 2. All elements except for the large cost dummy are unchanged.

Table A6: Large Cost Increases

(a) **Effects on $t+1$ Prices**

Dep. variable: $\sum_{h=0}^{1} \Delta p_{i,t+h}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	x = EBITDA				x = ICR				x = DSCR			
$\Delta mc_{i,t}$ ($\hat{\beta}_0$)	0.66***	0.55***	0.69***	0.61***	0.64***	0.54***	0.69***	0.60***	0.65***	0.54***	0.69***	0.59***
	(0.10)	(0.11)	(0.08)	(0.09)	(0.10)	(0.10)	(0.08)	(0.08)	(0.11)	(0.10)	(0.09)	(0.08)
Tight × $\Delta mc_{i,t}$ ($\hat{\beta}_1$)	0.08	0.09	0.13	0.05	0.14	0.18	0.09	0.11	0.05	0.11	0.08	0.12
	(0.18)	(0.18)	(0.14)	(0.12)	(0.16)	(0.18)	(0.12)	(0.14)	(0.20)	(0.21)	(0.15)	(0.16)
$\Delta p_{-i,t}$ ($\hat{\gamma}_0$)	0.26	0.50*			0.30*	0.48			0.30*	0.50*		
	(0.17)	(0.30)			(0.16)	(0.29)			(0.16)	(0.29)		
Tight × $\Delta p_{-i,t}$ ($\hat{\gamma}_1$)	-0.02	-0.12			-0.23	-0.30			-0.17	-0.26		
	(0.23)	(0.22)			(0.21)	(0.22)			(0.22)	(0.23)		
Tight	0.02**	0.02***	0.02**	0.02**	0.02***	0.02**	0.02*	0.01	0.03***	0.02***	0.02*	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Year FE	Y		Y		Y		Y		Y		Y	
Industry-Year FE		Y		Y		Y		Y		Y		Y
R^2	0.294	0.259	0.285	0.261	0.291	0.255	0.284	0.258	0.293	0.257	0.284	0.259
N	9,118	8,478	9,118	8,478	9,118	8,478	9,118	8,478	9,118	8,478	9,118	8,478
Firms	826	796	826	796	826	796	826	796	826	796	826	796
Two-digit Sectors	9		9		9		9		9		9	
Four-digit Industries		25		25		25		25		25		25
Weak IV F-test												
Kleibergen-Paap	15.25	7.42	28.61	28.73	6.97	8.31	9.15	10.53	11.93	7.12	25.99	34.51
Hansen J-test χ^2	7.027	3.034	4.609	2.932	7.472	6.210	4.026	1.799	6.045	4.016	4.057	1.950
p value	0.134	0.552	0.100	0.231	0.113	0.184	0.134	0.407	0.196	0.404	0.132	0.377
Financial Amplification												
$\hat{\beta}_0+\hat{\beta}_1$	0.74***	0.64***	0.82***	0.66***	0.77***	0.72***	0.77***	0.71***	0.69***	0.65***	0.77***	0.71***
$\hat{\gamma}_0+\hat{\gamma}_1$	0.25	0.39			0.07	0.17			0.13	0.24		

(b) **Effects on $t+2$ Prices**

Dep. variable: $\sum_{h=0}^{2} \Delta p_{i,t+h}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	x = EBITDA				x = ICR				x = DSCR			
$\Delta mc_{i,t}$ ($\hat{\beta}_0$)	0.44***	0.34***	0.51***	0.45***	0.44***	0.36***	0.55***	0.46***	0.43***	0.34***	0.54***	0.44***
	(0.11)	(0.11)	(0.09)	(0.10)	(0.11)	(0.10)	(0.08)	(0.09)	(0.11)	(0.10)	(0.08)	(0.09)
Tight × $\Delta mc_{i,t}$ ($\hat{\beta}_1$)	-0.07	0.02	0.11	-0.03	-0.13	-0.18	-0.13	-0.19	-0.06	-0.03	0.00	0.00
	(0.29)	(0.21)	(0.21)	(0.16)	(0.20)	(0.20)	(0.17)	(0.15)	(0.19)	(0.19)	(0.15)	(0.14)
$\Delta p_{-i,t}$ ($\hat{\gamma}_0$)	0.42*	1.13***			0.51**	1.07***			0.53**	1.12***		
	(0.22)	(0.41)			(0.23)	(0.38)			(0.23)	(0.38)		
Tight × $\Delta p_{-i,t}$ ($\hat{\gamma}_1$)	0.29	-0.10			-0.03	0.00			-0.08	-0.13		
	(0.38)	(0.27)			(0.24)	(0.25)			(0.23)	(0.23)		
Tight	0.02	0.03*	0.02	0.03**	0.04***	0.04***	0.04***	0.04***	0.03***	0.02*	0.03**	0.02
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Year FE	Y		Y		Y		Y		Y		Y	
Industry-Year FE		Y		Y		Y		Y		Y		Y
R^2	0.152	0.101	0.159	0.141	0.151	0.103	0.157	0.138	0.151	0.100	0.158	0.139
N	8,435	7,828	8,435	7,828	8,435	7,828	8,435	7,828	8,435	7,828	8,435	7,828
Firms	826	793	826	793	826	793	826	793	826	793	826	793
Two-digit Sectors	9		9		9		9		9		9	
Four-digit Industries		25		25		25		25		25		25
Weak IV F-test												
Kleibergen-Paap	11.26	7.10	25.81	33.19	6.28	7.36	9.85	9.98	15.98	7.30	26.57	35.18
Hansen J-test χ^2	5.131	1.727	2.475	1.383	6.152	4.061	2.383	1.780	4.899	3.506	2.226	1.255
p value	0.274	0.786	0.290	0.501	0.188	0.398	0.304	0.411	0.298	0.477	0.329	0.534
Financial Amplification												
$\hat{\beta}_0+\hat{\beta}_1$	0.37	0.36**	0.63***	0.42***	0.31	0.18	0.41**	0.27**	0.37**	0.31*	0.54***	0.44***
$\hat{\gamma}_0+\hat{\gamma}_1$	0.71*	1.03***			0.48*	1.07***			0.45*	0.99**		

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

Notes: xxx

Table A7: Effects of Financial Constraints on Future Prices

(a) **Effects on the COGS Margin**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		x = EBITDA				x = ICR				x = DSCR		
$\Delta mc_{i,t}$ ($\hat{\beta}_0$)	-0.37***	-0.38***	-0.31***	-0.33***	-0.36***	-0.36***	-0.30***	-0.32***	-0.36***	-0.37***	-0.31***	-0.33***
	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)
Tight × $\Delta mc_{i,t}$ ($\hat{\beta}_1$)	0.22***	0.24***	0.18***	0.14***	0.19**	0.19**	0.11**	0.12**	0.16*	0.20**	0.11*	0.12*
	(0.07)	(0.08)	(0.05)	(0.05)	(0.08)	(0.08)	(0.05)	(0.06)	(0.08)	(0.09)	(0.06)	(0.06)
$\Delta p_{-i,t}$ ($\hat{\gamma}_0$)	0.29***	0.35***			0.28***	0.33***			0.27***	0.34***		
	(0.09)	(0.13)			(0.08)	(0.12)			(0.08)	(0.12)		
Tight × $\Delta p_{-i,t}$ ($\hat{\gamma}_1$)	-0.24**	-0.25**			-0.22**	-0.22**			-0.21**	-0.25**		
	(0.10)	(0.10)			(0.10)	(0.10)			(0.10)	(0.11)		
Tight	0.02***	0.02***	0.01***	0.01***	0.01***	0.02***	0.01**	0.01*	0.01***	0.01***	0.01**	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Year FE	Y		Y		Y		Y		Y		Y	
Industry-Year FE		Y		Y		Y		Y		Y		Y
R^2	0.089	0.064	0.100	0.090	0.080	0.059	0.096	0.084	0.076	0.045	0.090	0.075
N	9,703	9,033	9,703	9,033	9,703	9,033	9,703	9,033	9,703	9,033	9,703	9,033
Firms	826	797	826	797	826	797	826	797	826	797	826	797
Two-digit Sectors	9		9		9		9		9		9	
Four-digit Industries		25		25		25		25		25		25
Weak IV F-test												
Kleibergen-Paap	14.71	9.94	27.17	25.93	6.77	7.42	9.86	11.45	13.35	9.70	24.26	27.43
Hansen J-test χ^2	5.701	2.727	5.526	1.741	2.375	2.376	0.692	0.397	2.837	2.889	0.594	0.378
p value	0.223	0.605	0.063	0.419	0.667	0.667	0.708	0.820	0.585	0.577	0.743	0.828
Financial Amplification												
$\hat{\beta}_0 + \hat{\beta}_1$	-0.149**	-0.138**	-0.134***	-0.185***	-0.178**	-0.177**	-0.195***	-0.203***	-0.202***	-0.176**	-0.196***	-0.204***
$\hat{\gamma}_0 + \hat{\gamma}_1$	0.051	0.095			0.057	0.101			0.069	0.088		

(b) **Effects on the EBITDA Margin**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		x = EBITDA				x = ICR				x = DSCR		
$\Delta mc_{i,t}$ ($\hat{\beta}_0$)	-0.20***	-0.20***	-0.18***	-0.18***	-0.22***	-0.21***	-0.19***	-0.20***	-0.22***	-0.23***	-0.19***	-0.21***
	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Tight × $\Delta mc_{i,t}$ ($\hat{\beta}_1$)	0.14	0.17	0.16*	0.14*	0.28*	0.28*	0.21*	0.24*	0.23*	0.27**	0.19*	0.21**
	(0.14)	(0.13)	(0.09)	(0.08)	(0.16)	(0.15)	(0.12)	(0.12)	(0.12)	(0.12)	(0.10)	(0.10)
$\Delta p_{-i,t}$ ($\hat{\gamma}_0$)	0.20**	0.13			0.22***	0.09			0.22**	0.13		
	(0.09)	(0.12)			(0.08)	(0.11)			(0.09)	(0.11)		
Tight × $\Delta p_{-i,t}$ ($\hat{\gamma}_1$)	-0.13	-0.19			-0.28	-0.28			-0.25*	-0.30**		
	(0.18)	(0.16)			(0.20)	(0.19)			(0.14)	(0.13)		
Tight	0.01***	0.01***	0.01	0.01	0.01**	0.01***	0.00	0.00	0.01**	0.01**	0.00	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Year FE	Y		Y		Y		Y		Y		Y	
Industry-Year FE		Y		Y		Y		Y		Y		Y
R^2	0.021	0.017	0.013	0.018	-0.017	-0.015	-0.004	-0.003	-0.017	-0.024	-0.009	-0.009
N	9,702	9,030	9,702	9,030	9,702	9,030	9,702	9,030	9,702	9,030	9,702	9,030
Firms	826	797	826	797	826	797	826	797	826	797	826	797
Two-digit Sectors	9		9		9		9		9		9	
Four-digit Industries		25		25		25		25		25		25
Weak IV F-test												
Cragg-Donald	64.03	59.01	235.50	233.91	60.82	60.96	217.71	211.84	68.12	62.80	230.87	233.38
Kleibergen-Paap	15.15	10.05	27.35	25.67	6.78	7.56	9.86	11.33	13.31	9.83	24.37	27.45
Hansen J-test χ^2	5.683	5.600	3.388	2.270	5.838	6.250	1.103	1.154	5.024	3.795	2.038	2.349
p value	0.224	0.231	0.184	0.321	0.212	0.181	0.576	0.562	0.285	0.434	0.361	0.309
Financial Amplification												
$\hat{\beta}_0 + \hat{\beta}_1$	-0.06	-0.03	-0.02	-0.05	0.06	0.07	0.03	0.04	0.01	0.04	-0.01	0.00
$\hat{\gamma}_0 + \hat{\gamma}_1$	0.07	-0.06			-0.06	-0.18			-0.03	-0.16		

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

Notes: xxx

Table A8: Effects of Financial Constraints on Profit Margins

(a) **Effects on $t+0$ Output**

Dep. variable: $\Delta y_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		x = EBITDA				x = ICR				x = DSCR		
$\Delta mc_{i,t}$ ($\hat{\beta}_0$)	-0.44***	-0.37***	-0.34***	-0.30***	-0.37***	-0.33***	-0.30***	-0.27***	-0.34**	-0.29**	-0.28***	-0.24**
	(0.11)	(0.12)	(0.09)	(0.10)	(0.11)	(0.11)	(0.09)	(0.09)	(0.13)	(0.13)	(0.10)	(0.10)
Tight × $\Delta mc_{i,t}$ ($\hat{\beta}_1$)	0.56	0.31	0.16	0.00	0.35	0.32	-0.08	-0.09	0.10	0.04	-0.17	-0.23
	(0.36)	(0.34)	(0.23)	(0.19)	(0.35)	(0.33)	(0.24)	(0.22)	(0.27)	(0.27)	(0.20)	(0.19)
$\Delta p_{-i,t}$ ($\hat{\gamma}_0$)	0.21	0.16			0.04	0.01			-0.02	-0.04		
	(0.24)	(0.36)			(0.23)	(0.34)			(0.28)	(0.37)		
Tight × $\Delta p_{-i,t}$ ($\hat{\gamma}_1$)	-0.98**	-0.65			-0.79*	-0.76*			-0.41	-0.36		
	(0.46)	(0.42)			(0.47)	(0.44)			(0.30)	(0.31)		
Tight	-0.01	-0.02*	-0.03**	-0.03**	0.01	-0.00	-0.01	-0.01	-0.00	-0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Year FE	Y		Y		Y		Y		Y		Y	
Industry-Year FE		Y		Y		Y		Y		Y		Y
R^2	0.042	0.053	0.061	0.064	0.051	0.046	0.068	0.062	0.064	0.059	0.070	0.063
N	9,738	9,065	9,738	9,065	9,738	9,065	9,738	9,065	9,738	9,065	9,738	9,065
Firms	826	797	826	797	826	797	826	797	826	797	826	797
Two-digit Sectors	9		9		9		9		9		9	
Four-digit Industries		25		25		25		25		25		25
Weak IV F-test	15.09	10.00	27.36	25.71	7.00	7.70	9.89	11.35	13.38	9.74	24.37	27.45
Hansen J-test χ^2	1.520	4.096	0.850	2.028	1.516	1.508	0.971	1.142	1.602	2.015	1.331	1.081
p value	0.823	0.393	0.654	0.363	0.824	0.825	0.615	0.565	0.808	0.733	0.514	0.583
Financial Amplification												
$\hat{\beta}_0 + \hat{\beta}_1$	0.11	-0.06	-0.18	-0.30	-0.02	-0.01	-0.37	-0.36	-0.23	-0.25	-0.44**	-0.47***
$\hat{\gamma}_0 + \hat{\gamma}_1$	-0.77	-0.49			-0.75	-0.75			-0.43	-0.40		

(b) **Effects on $t+1$ Output**

Dep. variable: $\Sigma_{h=0}^{1} \Delta y_{i,t+h}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		x = EBITDA				x = ICR				x = DSCR		
$\Delta mc_{i,t}$ ($\hat{\beta}_0$)	-0.58***	-0.48***	-0.39***	-0.37***	-0.52***	-0.44***	-0.31***	-0.33***	-0.46***	-0.39***	-0.26**	-0.27**
	(0.14)	(0.13)	(0.11)	(0.11)	(0.14)	(0.13)	(0.11)	(0.11)	(0.16)	(0.15)	(0.12)	(0.12)
Tight × $\Delta mc_{i,t}$ ($\hat{\beta}_1$)	-0.08	-0.34	0.16	-0.19	-0.36	-0.49	-0.38	-0.43	-0.49	-0.59	-0.52*	-0.62**
	(0.52)	(0.48)	(0.29)	(0.30)	(0.48)	(0.46)	(0.31)	(0.31)	(0.36)	(0.37)	(0.28)	(0.28)
$\Delta p_{-i,t}$ ($\hat{\gamma}_0$)	0.72**	1.15**			0.62*	1.12**			0.53	1.06*		
	(0.33)	(0.58)			(0.34)	(0.55)			(0.38)	(0.55)		
Tight × $\Delta p_{-i,t}$ ($\hat{\gamma}_1$)	-0.08	0.25			0.34	0.52			0.67	0.81		
	(0.71)	(0.64)			(0.70)	(0.66)			(0.49)	(0.50)		
Tight	-0.03	-0.04**	-0.03*	-0.03*	-0.03*	-0.03	-0.02	-0.01	-0.05***	-0.05***	-0.02	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Year FE	Y		Y		Y		Y		Y		Y	
Industry-Year FE		Y		Y		Y		Y		Y		Y
R^2	0.015	0.007	0.025	0.027	0.017	0.009	0.029	0.025	0.020	0.010	0.026	0.020
N	8,883	8,264	8,883	8,264	8,883	8,264	8,883	8,264	8,883	8,264	8,883	8,264
Firms	826	795	826	795	826	795	826	795	826	795	826	795
Two-digit Sectors	9		9		9		9		9		9	
Four-digit Industries		25		25		25		25		25		25
Weak IV F-test	13.79	7.05	27.43	27.72	12.56	7.98	9.47	10.98	10.92	7.01	24.37	31.67
Hansen J-test χ^2	5.235	3.253	2.831	2.672	2.359	0.923	0.740	0.747	4.047	1.580	0.779	0.458
p value	0.264	0.516	0.243	0.263	0.670	0.921	0.691	0.688	0.400	0.812	0.678	0.795
Financial Amplification												
$\hat{\beta}_0 + \hat{\beta}_1$	-0.66	-0.82*	-0.23	-0.56*	-0.88*	-0.92**	-0.70**	-0.75**	-0.96***	-0.99***	-0.79***	-0.89***
$\hat{\gamma}_0 + \hat{\gamma}_1$	0.64	1.40*			0.96	1.64**			1.20**	1.87***		

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

Notes: xxx

Table A9: Effects of Financial Constraints on Output

Dep. variable: $\ln\left(1+\frac{\text{Debt}_{i,t}}{\text{Assets}_{i,t}}\right)$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	x = EBITDA				x = ICR				x = DSCR			
$\Delta mc_{i,t}$ ($\hat{\beta}_0$)	-0.00	0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Tight × $\Delta mc_{i,t}$ ($\hat{\beta}_1$)	-0.03	-0.02	-0.02*	-0.02	-0.05***	-0.05***	-0.03**	-0.03**	-0.03*	-0.03*	-0.02**	-0.03**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
$\Delta p_{-i,t}$ ($\hat{\gamma}_0$)	0.01	-0.02			0.00	-0.02			0.00	-0.02		
	(0.01)	(0.02)			(0.01)	(0.03)			(0.01)	(0.03)		
Tight × $\Delta p_{-i,t}$ ($\hat{\gamma}_1$)	0.02	0.02			0.05**	0.06**			0.03	0.03		
	(0.02)	(0.02)			(0.02)	(0.02)			(0.02)	(0.02)		
Tight	0.00**	0.00***	0.00***	0.00***	0.00	0.00	0.00***	0.00**	0.00**	0.00**	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Year FE	Y		Y		Y		Y		Y		Y	
Industry-Year FE		Y		Y		Y		Y		Y		Y
R^2	-0.025	-0.017	-0.015	-0.011	-0.055	-0.065	-0.024	-0.036	-0.024	-0.025	-0.017	-0.022
N	9,738	9,065	9,738	9,065	9,738	9,065	9,738	9,065	9,738	9,065	9,738	9,065
Firms	826	797	826	797	826	797	826	797	826	797	826	797
Two-digit Sectors	9		9		9		9		9		9	
Four-digit Industries		25		25		25		25		25		25
Weak IV F-test	15.09	10.00	27.36	25.71	7.00	7.70	9.89	11.35	13.38	9.74	24.37	27.45
Hansen J-test χ^2	3.819	4.378	1.653	4.592	4.611	4.316	1.517	3.155	3.998	4.545	2.640	4.305
p value	0.431	0.357	0.438	0.101	0.330	0.365	0.468	0.207	0.406	0.337	0.267	0.116
Financial Amplification												
$\hat{\beta}_0+\hat{\beta}_1$	-0.03	-0.02	-0.02**	-0.02*	-0.05***	-0.05***	-0.03***	-0.03**	-0.03*	-0.03*	-0.02**	-0.03**
$\hat{\gamma}_0+\hat{\gamma}_1$	0.03	0.00			0.05**	0.04			0.03	0.01		

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

Notes: xxx

Table A10: Effects of Financial Constraints on Leverage

Dep.: $\sum_{h=0}^{F}(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t+h}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$F=1$						$F=2$					
	EBITDA		ICR		DSCR		EBITDA		ICR		DSCR	
$(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t}$	0.75***	0.71***	0.76***	0.71***	0.76***	0.71***	0.61***	0.62***	0.62***	0.62***	0.61***	0.61***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Tight × $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t}$	0.07*	-0.00	0.03	-0.01	0.02	0.01	0.02	-0.03	-0.01	-0.09*	0.05	-0.01
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.06)	(0.06)	(0.05)	(0.04)	(0.06)	(0.05)
$(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t-1}$	-0.19***	-0.17***	-0.17***	-0.16***	-0.18***	-0.17***	-0.24***	-0.22***	-0.24***	-0.22***	-0.24***	-0.22***
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Tight × $(x^{\text{mj}}\Delta\rho^{\text{mj}})_{i,t-1}$	0.00	-0.01	-0.07	-0.07	-0.01	-0.03	0.03	0.02	0.03	0.02	0.04	0.02
	(0.06)	(0.05)	(0.05)	(0.04)	(0.03)	(0.03)	(0.06)	(0.05)	(0.06)	(0.04)	(0.05)	(0.04)
Tight	-0.00	-0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Year FE	Y		Y		Y		Y		Y		Y	
Industry-Year FE		Y		Y		Y		Y		Y		Y
R^2	0.695	0.753	0.695	0.754	0.695	0.753	0.673	0.744	0.673	0.745	0.673	0.744
N	8,806	8,196	8,806	8,196	8,806	8,196	8,000	7,437	8,000	7,437	8,000	7,437
Firms	826	796	826	796	826	796	826	792	826	792	826	792
Two-digit Sectors	9		9		9		9		9		9	
Four-digit Industries		25		25		25		25		25		25

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

Notes: All

Table A11: Persistence of Input Cost Increases

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. variable: $\Delta p_{i,t}$	x = EBITDA				x = ICR				x = DSCR			
$\Delta mc_{i,t}$ $(\hat{\beta}_0)$	0.52^{***}	0.52^{***}	0.68^{***}	0.64^{***}	0.52^{***}	0.53^{***}	0.67^{***}	0.63^{***}	0.52^{***}	0.51^{***}	0.68^{***}	0.63^{***}
	(0.09)	(0.09)	(0.05)	(0.06)	(0.09)	(0.10)	(0.06)	(0.06)	(0.09)	(0.10)	(0.06)	(0.06)
Tight × $\Delta mc_{i,t}$ $(\hat{\beta}_1)$	0.21^{***}	0.23^{***}	0.21^{***}	0.14^{***}	0.17^{**}	0.17^{*}	0.10^{*}	0.13^{**}	0.14^{*}	0.19^{**}	0.08	0.12^{*}
	(0.08)	(0.08)	(0.06)	(0.05)	(0.08)	(0.09)	(0.05)	(0.06)	(0.09)	(0.09)	(0.06)	(0.06)
Small × $\Delta mc_{i,t}$	0.20^{**}	0.18^{*}	0.02	0.06	0.22^{**}	0.19^{*}	0.08	0.10	0.22^{**}	0.20^{*}	0.08	0.10
	(0.09)	(0.10)	(0.06)	(0.06)	(0.10)	(0.11)	(0.06)	(0.06)	(0.10)	(0.11)	(0.06)	(0.06)
$\Delta p_{-i,t}$ $(\hat{\gamma}_0)$	0.48^{***}	0.59^{***}			0.47^{***}	0.56^{***}			0.48^{***}	0.59^{***}		
	(0.14)	(0.20)			(0.14)	(0.20)			(0.14)	(0.20)		
Tight × $\Delta p_{-i,t}$ $(\hat{\gamma}_1)$	-0.22^{**}	-0.24^{**}			-0.20^{*}	-0.21^{*}			-0.20^{*}	-0.26^{**}		
	(0.10)	(0.10)			(0.11)	(0.11)			(0.10)	(0.11)		
Small × $\Delta p_{-i,t}$	-0.28^{**}	-0.27^{**}			-0.30^{**}	-0.28^{**}			-0.31^{**}	-0.29^{**}		
	(0.12)	(0.13)			(0.12)	(0.14)			(0.12)	(0.14)		
Tight	0.02^{***}	0.02^{***}	0.01^{**}	0.01^{***}	0.01^{***}	0.02^{***}	0.01^{**}	0.01^{*}	0.01^{***}	0.01^{***}	0.01^{**}	0.01^{*}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Small	0.00	0.00	0.00	-0.00	0.00	0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Year FE	Y		Y		Y		Y		Y		Y	
Industry-Year FE		Y		Y		Y		Y		Y		Y
R^2	0.671	0.658	0.690	0.682	0.670	0.660	0.690	0.678	0.669	0.654	0.691	0.677
N	9,569	8,914	9,569	8,914	9,569	8,914	9,569	8,914	9,569	8,914	9,569	8,914
Firms	826	797	826	797	826	797	826	797	826	797	826	797
Two-digit Sectors	9		9		9		9		9		9	
Four-digit Industries		25		25		25		25		25		25
Weak IV F-test												
Kleibergen-Paap	4.52	4.25	16.58	18.35	3.52	3.23	8.58	10.61	2.87	2.47	7.28	6.21
Hansen J-test χ^2	12.341	11.746	13.022	9.008	6.607	12.887	9.289	11.326	6.589	13.141	9.171	10.862
p value	0.055	0.068	0.005	0.029	0.359	0.045	0.026	0.010	0.361	0.041	0.027	0.012
Financial Amplification												
$\hat{\beta}_0 + \hat{\beta}_1$	0.73^{***}	0.75^{***}	0.90^{***}	0.78^{***}	0.69^{***}	0.70^{***}	0.78^{***}	0.76^{***}	0.66^{***}	0.70^{***}	0.76^{***}	0.75^{***}
$\hat{\gamma}_0 + \hat{\gamma}_1$	0.26^{**}	0.34^{*}			0.27^{*}	0.35^{*}			0.28^{**}	0.33^{*}		

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

Notes: xxx

Table A12: Effects of Financial Constraints with Size Controls

B Baseline Model

B.1 Intermediate Goods Producers

I derive the FOCs used in Section 2.2. When solving the full model in Section 4, I use value function iterations without deriving FOCs.

Objective. Assume that $\text{EBITDA}_{i,t}$ is always positive, which is true for usual parameter values.

$$\max_{\{P_{i,t},D_{i,t}\}} \mathrm{E}_t \sum_{h=0}^{\infty} \Lambda_{t,t+h} \frac{1}{P_{t+h}} \left[\text{Div}_{i,t+h} - (\mathscr{C}_{i,t+h} + \mathscr{E}_{i,t+h})\right], \tag{B.1}$$

subject to

$$\text{Nominal rigidities:} \quad \mathscr{C}_{i,t} = \frac{\tau_p}{2}\pi_{i,t}^2 P_t Y_t; \tag{B.2}$$

$$\text{Borrowing constraint:} \quad \phi_i \text{EBITDA}_{i,t} - D_{i,t} \geq 0; \tag{B.3}$$

$$\text{Equity/liquidity constraint:} \quad \mathscr{E}_{i,t} = -\tau_e \min(0, \text{Div}_{i,t}). \tag{B.4}$$

When there is no equity issuance:

$$\begin{aligned}\mathscr{L} = \mathrm{E}_t \sum_{h=0}^{\infty} \Lambda_{t,t+h} \frac{1}{P_{t+h}} \Big[&\text{Div}_{i,t+h} - (\mathscr{C}_{i,t+h} + \mathscr{E}_{i,t+h}) \\ &+ \xi_{i,t+h}^{ebc}(\phi_i \text{EBITDA}_{i,t+h} - D_{i,t+h}) + \xi_{i,t+h}^{div}\text{Div}_{i,t+h}\Big].\end{aligned} \tag{B.5}$$

Borrowing FOC. Let the two debt-related Lagrangian multipliers (in real terms) be $\xi_{i,t}^{ebc}$ and $\xi_{i,t}^{div}$. Differentiate w.r.t. $D_{i,t}$:

$$\xi_{i,t}^{ebc} = (1 + \xi_{i,t}^{div}) - \mathrm{E}_t \Lambda_{t,t+1}(1 + r_{i,t+1}^{b,r})(1 + \xi_{i,t+1}^{div}) \tag{B.6}$$

where $r_{i,t+1}^{b,r}$ is the real borrowing cost. The liquidity constraint means that $\xi_{i,t}^{div} \leq \tau_e$.

Pricing FOC. Standard FOC w.r.t. $P_{i,t}$:

$$\frac{\partial \text{EBITDA}_{i,t}}{\partial P_{i,t}} = Y_{i,t} + P_{i,t}\frac{\partial Y_{i,t}}{\partial P_{i,t}} - W_t \frac{\partial L_{i,t}}{\partial Y_{i,t}}\frac{\partial Y_{i,t}}{\partial P_{i,t}} = Y_{i,t} - Y_{i,t}\epsilon_{i,t} + W_t \frac{Y_{i,t}}{P_{i,t}}\epsilon_{i,t}\frac{\partial L_{i,t}}{\partial Y_{i,t}} \tag{B.7}$$

$$= Y_{i,t}(\epsilon_{i,t} - 1)\left[\frac{\epsilon_{i,t}}{\epsilon_{i,t}-1}\frac{\partial L_{i,t}}{\partial Y_{i,t}}\frac{W_t}{P_{i,t}} - 1\right] \tag{B.8}$$

Next,

$$\frac{(1 + \xi_{i,t}^{div} + \xi_{i,t}^{ebc}\phi_i)}{P_t}\frac{\partial \text{Div}_{i,t}}{\partial P_{i,t}} - \frac{1}{P_{i,t}}Y_t \tau_p \pi_{i,t} + \frac{1}{P_{i,t}}\mathrm{E}_t \Lambda_{t,t+1}\tau_p \pi_{i,t+1} Y_{t+1} = 0 \tag{B.9}$$

and because $\frac{\partial \text{EBITDA}_{i,t}}{\partial P_{i,t}} = \frac{\partial \text{Div}_{i,t}}{\partial P_{i,t}}$,

$$\pi_{i,t} = (1+\xi_{i,t}^{div} + \xi_{i,t}^{ebc}\phi_i)\frac{\epsilon_{i,t}-1}{\tau_p}\frac{P_{i,t}Y_{i,t}}{P_tY_t}\left[\mathscr{M}_{i,t}\frac{\partial L_{i,t}}{\partial Y_{i,t}}\frac{W_t}{P_{i,t}} - 1\right] + \mathrm{E}_t\,\Lambda_{t,t+1}\pi_{i,t+1} \tag{B.10}$$

Define $\kappa_{i,t} = \frac{\epsilon_{i,t}-1}{\tau_p}\frac{P_{i,t}Y_{i,t}}{P_tY_t}$,

$$\pi_{i,t} = (1+\xi_{i,t}^{div} + \xi_{i,t}^{ebc}\phi_i)\kappa_{i,t}\left[\mathscr{M}_{i,t}\frac{\partial L_{i,t}}{\partial Y_{i,t}}\frac{W_t}{P_{i,t}} - 1\right] + \mathrm{E}_t\,\Lambda_{t,t+1}\pi_{i,t+1} \tag{B.11}$$

Marginal costs. Define the nominal marginal cost $MC_{i,t}^n$ and the real marginal cost $MC_{i,t}^r$:

$$MC_{i,t}^n = \frac{\partial L_{i,t}}{\partial Y_{i,t}}W_t \tag{B.12}$$

$$MC_{i,t}^r = \frac{\partial L_{i,t}}{\partial Y_{i,t}}\frac{W_t}{P_t} \tag{B.13}$$

Note that

$$L_{i,t} = \left(\frac{Y_{i,t}+\omega_i}{A_{i,t}}\right)^{\frac{1}{1-\gamma}} \tag{B.14}$$

$$\frac{Y_{i,t}}{L_{i,t}}\frac{\partial L_{i,t}}{\partial Y_{i,t}} = \frac{1}{1-\gamma}\frac{Y_{i,t}}{Y_{i,t}+\omega_i} \tag{B.15}$$

$$\frac{\partial L_{i,t}}{\partial Y_{i,t}} = \frac{1}{1-\gamma}\frac{L_{i,t}}{Y_{i,t}+\omega_i} = \frac{1}{1-\gamma}(Y_{i,t}+\omega_i)^{\frac{\gamma}{1-\gamma}}A_{i,t}^{-\frac{1}{1-\gamma}} \tag{B.16}$$

$$mc_{i,t}^n = \ln\frac{1}{1-\gamma} + \frac{\gamma}{1-\gamma}\ln(Y_{i,t}+\omega_i) - \frac{1}{1-\gamma}a_{i,t} + W_t \tag{B.17}$$

where $Y_{i,t} = P_{i,t}^{-\epsilon}P_t^{\epsilon}Y_t$. Also have $\frac{\partial mc_{i,t}^n}{\partial y_{i,t}} = \frac{\gamma}{1-\gamma}\frac{Y_{i,t}}{Y_{i,t}+\omega_i}$.

B.2 Other Elements

Goods. Denote $\tilde{x}_{i,t} = x_{i,t} - x_t$, which is the gap between firm-level x and aggregate x.

When all firms have equal weights:

$$\tilde{y}_{i,t} = y_{i,t} - y_t = -\epsilon\tilde{p}_{i,t}, \tag{B.18}$$

where

$$Y_t = \left(\int_0^1 Y_{i,t}^{\frac{\epsilon-1}{\epsilon}}di\right)^{\frac{\epsilon}{\epsilon-1}}, \qquad P_t = \left(\int_0^1 P_{i,t}^{1-\epsilon}di\right)^{\frac{1}{1-\epsilon}}. \tag{B.19}$$

At the first order around the symmetric equilibrium,

$$0 = \int_0^1 \tilde{y}_{i,t} di, \qquad 0 = \int_0^1 \tilde{p}_{i,t} di, \qquad \pi_t = \int_0^1 \pi_{i,t} di. \tag{B.20}$$

Labor demand.

Assume some aggregate A_t and ω:

$$L_t = \int L_{i,t} di = \int \left(\frac{Y_{i,t} + \omega_i}{A_{i,t}} \right)^{\frac{1}{1-\gamma}} di = \int \left(\frac{P_t^{\epsilon}}{A_{i,t} P_{i,t}^{\epsilon}} Y_t + \frac{\omega_i}{A_{i,t}} \right)^{\frac{1}{1-\gamma}} di \tag{B.21}$$

$$= \left(\frac{Y_t + \omega}{A_t} \right)^{\frac{1}{1-\gamma}} \int \left[\frac{A_t}{A_{i,t}} \left[\left(\frac{P_{i,t}}{P_t} \right)^{-\epsilon} \frac{Y_t}{Y_t + \omega} + \frac{\omega_i}{Y_t + \omega} \right] \right]^{\frac{1}{1-\gamma}} di \tag{B.22}$$

$$= \left(\frac{Y_t + \omega}{A_t} \right)^{\frac{1}{1-\gamma}} \underbrace{\int \left[\frac{\tilde{A}_{i,t}^{-1}}{Y_t + \omega} \left(\tilde{P}_{i,t}^{-\epsilon} Y_t + \omega_i \right) \right]^{\frac{1}{1-\gamma}} di}_{\text{Misallocation}} \tag{B.23}$$

Define $\Delta_t = \int \left[\frac{\tilde{A}_{i,t}^{-1}}{Y_t+\omega} \left(\tilde{P}_{i,t}^{-\epsilon} Y_t + \omega_i \right) \right]^{\frac{1}{1-\gamma}} di$, which can be solved numerically fairly easily. Second-order approximation of Δ_t can be cumbersome, yet the intuition behind Δ_t is straightforward. Holding $A_{i,t}$ constant, when price dispersion is large, Δ_t increases. The increase in Δ_t is increasing in ϵ and γ and decreasing in ω.

C Alternative Pricing Models

C.1 Calvo Pricing

Objective. θ is the probability of not changing the price. Define the new objective function:

$$V_{t-1}(P_{i,t-1}, D_{i,t-1}) = \max_{\{P_{i,t}^*, D_{i,t}\}} \theta \left[\frac{[\text{Div}_{i,t} - \mathscr{E}_{i,t}]_{\mid P_{i,t-1}}}{P_t} + \mathrm{E}_t \Lambda_{t,t+1} V_t(P_{i,t-1}, D_{i,t}) \right]$$
$$+ (1-\theta) \left[\frac{[\text{Div}_{i,t} - \mathscr{E}_{i,t}]_{\mid P_{i,t}^*}}{P_t} + \mathrm{E}_t \Lambda_{t,t+1} V_t(P_{i,t}^*, D_{i,t}) \right] \tag{C.1}$$

subject to

$$\text{Borrowing constraint:} \quad \phi_i \text{EBITDA}_{i,t} - D_{i,t} \geq 0; \tag{C.2}$$
$$\text{Equity/liquidity constraint:} \quad \mathscr{E}_{i,t} = -\tau_e \min(0, \text{Div}_{i,t}). \tag{C.3}$$

Adding four costate variables: $\{\xi_{i,t}^{ebc}, \xi_{i,t}^{div}, \xi_{i,t}^{ebc,*}, \xi_{i,t}^{div,*}\}$. $\xi_{i,t}^{ebc,*}$ and $\xi_{i,t}^{div,*}$ are the Lagrangian multipliers on the two constraints when firm i is able to change its price to $P_{i,t}^*$. $\xi_{i,t}^{ebc}$ and $\xi_{i,t}^{div}$

are the Lagrangian multipliers on the constraints when firm i sticks to its old price $P_{i,t-1}$.

$$\begin{aligned}
&P_t V_{t-1}(P_{i,t-1}, D_{i,t-1}) && \text{(C.4)}\\
&= \max_{\{P^*_{i,t}, D_{i,t}\}} \theta \Big[[\mathrm{Div}_{i,t} - \mathscr{E}_{i,t}]_{|P_{i,t-1}} + P_t \mathrm{E}_t \Lambda_{t,t+1} V_t(P_{i,t-1}, D_{i,t}) \\
&\qquad + \xi^{ebc}_{i,t}(\phi_i \mathrm{EBITDA}_{i,t|P_{i,t-1}} - D_{i,t}) + \xi^{div}_{i,t} \mathrm{Div}_{i,t|P_{i,t-1}} \Big] \\
&\quad + (1-\theta) \Big[[\mathrm{Div}_{i,t} - \mathscr{E}_{i,t}]_{|P^*_{i,t}} + P_t \mathrm{E}_t \Lambda_{t,t+1} V_t(P^*_{i,t}, D_{i,t}) \\
&\qquad + \xi^{ebc,*}_{i,t}(\phi_i \mathrm{EBITDA}_{i,t|P^*_{i,t}} - D_{i,t}) + \xi^{div,*}_{i,t} \mathrm{Div}_{i,t|P^*_{i,t}} \Big] && \text{(C.5)}
\end{aligned}$$

Borrowing FOC. Define weighted average multipliers:

$$\bar{\xi}^{div}_{i,t} = \theta \xi^{div}_{i,t} + (1-\theta)\xi^{div,*}_{i,t}, \quad \bar{\xi}^{ebc}_{i,t} = \theta \xi^{ebc}_{i,t} + (1-\theta)\xi^{ebc,*}_{i,t} \tag{C.6}$$

FOC W.r.t. $D_{i,t-1}$ (note that this is independent of $P_{i,t-1}$):

$$P_t \frac{\partial V_{t-1}(P_{i,t-1}, D_{i,t-1})}{\partial D_{i,t-1}} = -(1 + r^b_{i,t})(1 + \bar{\xi}^{div}_{i,t}) \tag{C.7}$$

FOC W.r.t. $D_{i,t}$:

$$\begin{aligned}
0 &= (1 + \bar{\xi}^{div}_{i,t} - \bar{\xi}^{ebc}_{i,t}) + P_t \theta \mathrm{E}_t \Lambda_{t,t+1} \frac{\partial V_t(P_{i,t-1}, D_{i,t})}{\partial D_{i,t}} + P_t(1-\theta) \mathrm{E}_t \Lambda_{t,t+1} \frac{\partial V_t(P^*_{i,t}, D_{i,t})}{\partial D_{i,t}} && \text{(C.8)}\\
&= (1 + \bar{\xi}^{div}_{i,t} - \bar{\xi}^{ebc}_{i,t}) - \mathrm{E}_t \Lambda_{t,t+1} \frac{P_t}{P_{t+1}}(1 + r^b_{i,t+1})(1 + \bar{\xi}^{div}_{i,t+1}) && \text{(C.9)}
\end{aligned}$$

As before,

$$\bar{\xi}^{ebc}_{i,t} = (1 + \bar{\xi}^{div}_{i,t}) - \mathrm{E}_t \Lambda_{t,t+1}(1 + r^{b,r}_{i,t+1})(1 + \bar{\xi}^{div}_{i,t+1}) \tag{C.10}$$

where $\bar{\xi}^{div}_{i,t+1} < \tau_e$.

Pricing FOC. W.r.t. $P_{i,t-1}$:

$$\begin{aligned}
&\frac{P_t}{\theta} \frac{\partial V_{t-1}(P_{i,t-1}, D_{i,t-1})}{\partial P_{i,t-1}} \\
&= \frac{\partial \mathrm{EBIDTA}_{i,t|P_{i,t-1}}}{\partial P_{i,t-1}} + P_t \mathrm{E}_t \Lambda_{t,t+1} \frac{\partial V_t(P_{i,t-1}, D_{i,t})}{\partial P_{i,t-1}} + (\xi^{div}_{i,t} + \xi^{ebc}_{i,t}\phi_i) \frac{\partial \mathrm{EBIDTA}_{i,t|P_{i,t-1}}}{\partial P_{i,t-1}} \\
&= (1 + \xi^{div}_{i,t} + \xi^{ebc}_{i,t}\phi_i) \frac{\partial \mathrm{EBIDTA}_{i,t|P_{i,t-1}}}{\partial P_{i,t-1}} + P_t \mathrm{E}_t \Lambda_{t,t+1} \frac{\partial V_t(P_{i,t-1}, D_{i,t})}{\partial P_{i,t-1}} && \text{(C.11)}
\end{aligned}$$

W.r.t. $P^*_{i,t}$:

$$0 = (1+\xi^{div,*}_{i,t}+\xi^{ebc,*}_{i,t}\phi_i)\frac{\partial \text{EBIDTA}_{i,t\,|\,P^*_{i,t}}}{\partial P^*_{i,t}} + P_t\,\mathrm{E}_t\,\Lambda_{t,t+1}\frac{\partial V_t(P^*_{i,t},D_{i,t})}{\partial P^*_{i,t}} \tag{C.12}$$

Move the FOC w.r.t. $P_{i,t-1}$ forward by one period and evaluate at $P^*_{i,t}$. Note that $P^*_{i,t}$ is not an arbitrary choice. From the perspective of firm i at $t+k$, $P^*_{i,t}$ is the most recent reset price. The equation will not hold if I evaluate it at any other price.

$$\begin{aligned}
&\frac{\partial V_t(P^*_{i,t},D_{i,t})}{\partial P^*_{i,t}}\\
&= \frac{\theta(1+\xi^{div}_{i,t+1}+\xi^{ebc}_{i,t+1}\phi_i)}{P_{t+1}}\frac{\partial \text{EBIDTA}_{i,t+1\,|\,P^*_{i,t}}}{\partial P^*_{i,t}} + \theta\,\mathrm{E}_t\,\Lambda_{t+1,t+2}\frac{\partial V_{t+1}(P^*_{i,t},D_{i,t+1})}{\partial P^*_{i,t}}\\
&= \frac{\theta(1+\xi^{div}_{i,t+1}+\xi^{ebc}_{i,t+1}\phi_i)}{P_{t+1}}\frac{\partial \text{EBIDTA}_{i,t+1\,|\,P^*_{i,t}}}{\partial P^*_{i,t}}\\
&\quad + \mathrm{E}_t\,\Lambda_{t+1,t+2}\frac{\theta^2(1+\xi^{div}_{i,t+2}+\xi^{ebc}_{i,t+2}\phi_i)}{P_{t+2}}\frac{\partial \text{EBIDTA}_{i,t+2\,|\,P^*_{i,t}}}{\partial P^*_{i,t}}\\
&\quad + \mathrm{E}_t\,\Lambda_{t+1,t+3}\frac{\theta^3(1+\xi^{div}_{i,t+3}+\xi^{ebc}_{i,t+3}\phi_i)}{P_{t+3}}\frac{\partial \text{EBIDTA}_{i,t+3\,|\,P^*_{i,t}}}{\partial P^*_{i,t}}\\
&\quad + \cdots
\end{aligned} \tag{C.13}$$

Define $\xi^*_{i,t}=\xi^{div,*}_{i,t}+\xi^{ebc,*}_{i,t}\phi_i$ and $\xi_{i,t}=\xi^{div}_{i,t}+\xi^{ebc}_{i,t}\phi_i$. Combine the FOCs:

$$0=(1+\xi^*_{i,t})\frac{\partial \text{EBIDTA}_{i,t\,|\,P^*_{i,t}}}{\partial P^*_{i,t}} + \mathrm{E}_t\sum_{k=1}^{\infty}\Lambda_{t+1,t+k}\theta^k(1+\xi_{i,t+k})\frac{P_t}{P_{t+k}}\frac{\partial \text{EBIDTA}_{i,t+h\,|\,P^*_{i,t}}}{\partial P^*_{i,t}} \tag{C.14}$$

The limiting case. Unlike in the Rotemberg case, in the Calvo case there are two sets of multipliers. $\xi^*_{i,t}$ is the shadow value of internal cash flows evaluated at the reset price at t, while $\xi_{i,t}$ is the shadow value evaluated at the most recent rest price. Nonetheless, the intuition behind propositions 1 and 2 is the same. If $\xi^*_{i,t}$ is much higher than future $\xi_{i,t}$, discounted by the probability of not being able to reset price (θ^k), then firm i will choose $P^*_{i,t}$ such that $\frac{\partial \text{EBIDTA}_{i,t\,|\,P^*_{i,t}}}{\partial P^*_{i,t}}$ is closer to zero. In other words, firm i's desired reset price will be closer to its optimal flexible price. Therefore, propositions 1 and 2 still hold if I redefine the limiting case as (i) $\xi^*_{i,t}\to\infty$ and (ii) $\forall h$, $\frac{\xi^*_{i,t}}{\xi_{i,t+h}}\to\infty$.

C.2 Menu-Cost Models

Objective. In order to draw analytical results, I generalize menu-cost models to a Calvo model above but with endogenous $\theta_{i,t}$. $\theta_{i,t}$ is a function of the gap between the current price and the optimal reset price (both in log terms). Define the gap $x_{i,t}$, as the log difference between the two prices $(p_{i,t-1} - p^*_{i,t})$. The functional form is given by:

$$\theta_{i,t} = \theta(x_{i,t}) = \theta^o - \phi x^2_{i,t}. \tag{C.15}$$

where θ^o is the upper bound of $\theta_{i,t}$. The intuition is simple: the larger is the absolute price gap, the smaller is $\theta_{i,t}$. This captures the essence of the selection effect in menu-cost models. More importantly, Gagliardone et al. (2024) find that the quadratic generalized hazard function (GHF) can well describe the empirical GHF.

The new objective function is:

$$\begin{aligned} V_{t-1}(P_{i,t-1}, D_{i,t-1}) = \max_{\{P^*_{i,t}, D_{i,t}\}} \; & \theta_{i,t}\left[\frac{[\mathrm{Div}_{i,t} - \mathcal{E}_{i,t}]_{\,|\,P_{i,t-1}}}{P_t} + \mathrm{E}_t\,\Lambda_{t,t+1} V_t(P_{i,t-1}, D_{i,t})\right] \\ & + (1-\theta_{i,t})\left[\frac{[\mathrm{Div}_{i,t} - \mathcal{E}_{i,t}]_{\,|\,P^*_{i,t}}}{P_t} + \mathrm{E}_t\,\Lambda_{t,t+1} V_t(P^*_{i,t}, D_{i,t})\right] \end{aligned} \tag{C.16}$$

subject to

$$\phi_i \mathrm{EBITDA}_{i,t} \geq D_{i,t}, \tag{C.17}$$

$$\mathcal{E}_{i,t} = -\tau_e \min(0, \mathrm{Div}_{i,t}). \tag{C.18}$$

Borrowing FOC. The borrowing FOC is exactly the same as in the standard Calvo case.

Pricing FOC. W.r.t. $P_{i,t-1}$:

$$\begin{aligned} & \frac{P_t}{\theta_{i,t}} \frac{\partial V_{t-1}(P_{i,t-1}, D_{i,t-1})}{\partial P_{i,t-1}} \\ & = (1 + \xi^{div}_{i,t} + \xi^{ebc}_{i,t}\phi_i)\frac{\partial \mathrm{EBIDTA}_{i,t\,|\,P_{i,t-1}}}{\partial P_{i,t-1}} + P_t\,\mathrm{E}_t\,\Lambda_{t,t+1}\frac{\partial V_t(P_{i,t-1}, D_{i,t})}{\partial P_{i,t-1}} \\ & \quad + \frac{(p_{i,t-1} - p^*_{i,t})\theta'_{i,t}}{P_{i,t-1}\theta_{i,t}}\Big[[\mathrm{Div}_{i,t} - \mathcal{E}_{i,t}]_{\,|\,P_{i,t-1}} + P_t\,\mathrm{E}_t\,\Lambda_{t,t+1} V_t(P_{i,t-1}, D_{i,t}) \\ & \qquad - [\mathrm{Div}_{i,t} - \mathcal{E}_{i,t}]_{\,|\,P^*_{i,t}} - P_t\,\mathrm{E}_t\,\Lambda_{t,t+1} V_t(P^*_{i,t}, D_{i,t})\Big] \end{aligned} \tag{C.19}$$

W.r.t. $P^*_{i,t}$:

$$\begin{aligned} 0 = {} & (1 + \xi^{div,*}_{i,t} + \xi^{ebc,*}_{i,t}\phi_i)\frac{\partial \mathrm{EBIDTA}_{i,t\,|\,P^*_{i,t}}}{\partial P^*_{i,t}} + P_t\,\mathrm{E}_t\,\Lambda_{t,t+1}\frac{\partial V_t(P^*_{i,t}, D_{i,t})}{\partial P^*_{i,t}} \\ & + \frac{(p^*_{i,t} - p_{i,t-1})\theta'_{i,t}}{P^*_{i,t}(1-\theta_{i,t})}\Big[[\mathrm{Div}_{i,t} - \mathcal{E}_{i,t}]_{\,|\,P_{i,t-1}} + P_t\,\mathrm{E}_t\,\Lambda_{t,t+1} V_t(P_{i,t-1}, D_{i,t}) \\ & \qquad - [\mathrm{Div}_{i,t} - \mathcal{E}_{i,t}]_{\,|\,P^*_{i,t}} - P_t\,\mathrm{E}_t\,\Lambda_{t,t+1} V_t(P^*_{i,t}, D_{i,t})\Big] \end{aligned} \tag{C.20}$$

Define $\tau_{i,t} = \frac{P^*_{i,t} - P_{i,t-1}}{P_t}\theta'_{i,t}\Big[[\mathrm{Div}_{i,t} - \mathcal{E}_{i,t}]_{\,|\,P_{i,t-1}} + P_t\,\mathrm{E}_t\,\Lambda_{t,t+1} V_t(P_{i,t-1}, D_{i,t}) - [\mathrm{Div}_{i,t} - \mathcal{E}_{i,t}]_{\,|\,P^*_{i,t}} -$

$P_t \mathrm{E}_t \Lambda_{t,t+1} V_t(P^*_{i,t}, D_{i,t})\Big]$. $\tau_{i,t}$ captures the tension caused by the gap between the current price and the desired reset price.

Move the FOC w.r.t. $P_{i,t-1}$ forward by one period and evaluate at $P^*_{i,t}$.

$$
\begin{aligned}
&\frac{\partial V_t(P^*_{i,t}, D_{i,t})}{\partial P^*_{i,t}} \\
&= \frac{\theta_{i,t+1}(1+\xi^{div}_{i,t+1}+\xi^{ebc}_{i,t+1}\phi_i)}{P_{t+1}} \frac{\partial \mathrm{EBIDTA}_{i,t+1\,|\,P^*_{i,t}}}{\partial P^*_{i,t}} - \frac{\tau_{i,t+1}}{P^*_{i,t}} + \theta_{i,t+1} \mathrm{E}_t \Lambda_{t+1,t+2} \frac{\partial V_{t+1}(P^*_{i,t}, D_{i,t+1})}{\partial P^*_{i,t}} \\
&= \frac{\theta_{i,t+1}(1+\xi^{div}_{i,t+1}+\xi^{ebc}_{i,t+1}\phi_i)}{P_{t+1}} \frac{\partial \mathrm{EBIDTA}_{i,t+1\,|\,P^*_{i,t}}}{\partial P^*_{i,t}} - \frac{\tau_{i,t+1}}{P^*_{i,t}} \\
&\quad + \mathrm{E}_t \Lambda_{t+1,t+2} \frac{\Pi^2_{h=1}\theta_{i,t+h}(1+\xi^{div}_{i,t+2}+\xi^{ebc}_{i,t+2}\phi_i)}{P_{t+2}} \frac{\partial \mathrm{EBIDTA}_{i,t+2\,|\,P^*_{i,t}}}{\partial P^*_{i,t}} - \mathrm{E}_t \Lambda_{t+1,t+2}\theta_{i,t+2} \frac{\tau_{i,t+2}}{P^*_{i,t}} \\
&\quad + \mathrm{E}_t \Lambda_{t+1,t+3} \frac{\Pi^3_{h=1}\theta_{i,t+h}(1+\xi^{div}_{i,t+3}+\xi^{ebc}_{i,t+3}\phi_i)}{P_{t+3}} \frac{\partial \mathrm{EBIDTA}_{i,t+3\,|\,P^*_{i,t}}}{\partial P^*_{i,t}} - \mathrm{E}_t \Lambda_{t+1,t+3}\Pi^3_{h=2}\theta_{i,t+h} \frac{\tau_{i,t+3}}{P^*_{i,t}} \\
&\quad + \cdots
\end{aligned}
\tag{C.21}
$$

Define $\xi^*_{i,t} = \xi^{div,*}_{i,t} + \xi^{ebc,*}_{i,t}\phi_i$ and $\xi_{i,t} = \xi^{div}_{i,t} + \xi^{ebc}_{i,t}\phi_i$. Combine the FOCs:

$$
\begin{aligned}
0 = (1+\xi^*_{i,t}) \frac{\partial \mathrm{EBIDTA}_{i,t\,|\,P^*_{i,t}}}{\partial P^*_{i,t}} + \frac{\tau_{i,t}}{P^*_{i,t}(1-\theta_{i,t})} - \mathrm{E}_t \sum_{k=1}^{\infty} \Lambda_{t+1,t+k}\Pi^k_{h=2}\theta_{i,t+h} \frac{\tau_{i,t+k}}{P^*_{i,t}} \\
+ \mathrm{E}_t \sum_{k=1}^{\infty} \Lambda_{t+1,t+k}\Pi^k_{h=1}\theta_{i,t+h}(1+\xi_{i,t+k}) \frac{P_t}{P_{t+k}} \frac{\partial \mathrm{EBIDTA}_{i,t+h\,|\,P^*_{i,t}}}{\partial P^*_{i,t}}
\end{aligned}
\tag{C.22}
$$

The limiting case. So long as $\tau_{i,t}$ is bounded, the limiting case does not change. Under usual parameter assumptions, all terms, including $\theta'_{i,t} = -\phi x_{i,t}$, are be bounded. Therefore, the limiting case is the same as in the Calvo case.

Now, what if $\theta_{i,t}$ is not always differentiable? E.g., in the early menu-cost models with a constant fixed cost, $\theta_{i,t} = 0$ when the old price is within the Ss bands, while $\theta_{i,t} = 1$ when the old price hits the bands. There is generally no analytical solution, but the intuition remains the same. Each optimal reset price is still a weighted average of current and future marginal costs. With the selection effect, firms put less weight on large future margin cost shocks during which firms are more likely to reset prices. Yet the optimal reset price is still a weighted average between the current and future marginal costs, and financial constraints alter the intertemporal weighting in the same way.

D Data Appendix

D.1 Data Cleaning

Negative values. At the firm level, I exclude firms who report non-positive sales, costs, assets, or borrowings. At the product level, I exclude products with non-positive sales.

Decimal point errors. Decimal points are sometimes misplaced. Observe that nominal sales values often look correct, but quantities occasionally look very erroneous.

- Select the "correct" subset where the log price change for product x, $\Delta p_{x,t}$, is between $-\ln 3$ and $\ln 3$. I assume that data in this subset are correct.
- I calculated the 10th and 90th percentiles of price changes $\Delta p_{x,t}$ and quantity changes $\Delta y_{x,t}$ within this subset.
- For all observations outside of the "correct" subset, I test if the decimal point is misplaced. Assume that for product z, output is mistakenly multiplied by 100 (misplaced by 2 units), I calculate both $(\Delta p_{z,t} + \ln 100)$ and $(\Delta y_{z,t} - \ln 100)$. If (i) $(\Delta p_{z,t} + \ln 100)$ is within the 10th and 90th percentile of price changes in the "correct" subset and (ii) $(\Delta y_{z,t} - \ln 100)$ is within the 10th and 90th percentile of quantity changes in the "correct" subset, I accept the hypothesis. If either condition is not satisfied, I reject the hypothesis.
- I do the testing for all observations. Possible decimal point misplacement ranges from -6 to +6 units.

Winsorization. Product-level price changes are truncated between $-\ln 3$ and $\ln 3$. Then they are winsorized at the 0.5th and 99.5th percentiles. The EBITDA ratio is capped between -20% and 100%. The ICR and DSCR are capped between 1% and $+\infty$. Other non-price variables are winsorized at the 1st and 99th percentiles.

Data interpolation. Given that the right hand side of my regressions include up to two lags, one missing data point can cost up to three observations in the regression sample. This may further interact with the fact that I require at least 8 years for each firm and 6 firms in each sector-year pair, costing more observations. For this reason, a little bit interpolation may improve the sample size disproportionally.

However, interpolation may also cause severe biases. Therefore, I do not interpolate any data before I have the final panel for regressions.

When the final panel is ready, I interpolate all right-hand side variables up to 1 period, i.e., if $x_{i,t-1}$ and $x_{i,t+1}$ are available but $x_{i,t}$ is missing, I assume $x_{i,t} = \frac{x_{i,t-1}+x_{i,t+1}}{2}$. Note that for all price variables, I use the changes instead of the levels. So one missing data point creates two consecutive missing changes, and these are never interpolated. Given the strict requirements, interpolated data only account for about 1% in the regression sample, but the inclusion of them increases the sample by more than 3%.