Real Price Rigidity and Investment Irreversibility in Customer Markets: Evidence from Credit Supply Shocks

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Abstract

This paper argues that investment irreversibility leads to greater real price rigidity by strengthening the customer-market incentive. In a simple model, predictable demand from a customer base insures firms against future losses from irreversible capital after bad idiosyncratic demand shocks. Thus, firms with more irreversible capital forgo profits today by selling more output to invest in a larger customer base. But when financial constraints tighten and make current profits more valuable, these firms reduce customer investment more sharply, which puts more upward pressure on prices and markups. This behavior makes markups more countercyclical and thus causes greater real price rigidity. I find evidence consistent with this mechanism using producer price microdata and the bankruptcy of Lehman Brothers as a natural experiment in the credit supplied to firms. After credit contractions, firms in low-irreversibility industries cut prices while firms in high-irreversibility industries do not. Markups also rise temporarily in high-irreversibility industries relative to low-irreversibility industries. A back-of-the-envelope exercise implies that credit contractions lower aggregate prices by almost 40% less than they would if prices in all industries responded like prices in the least irreversible industry.

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1 Introduction

Price rigidity shapes the comovement of inflation with aggregate output. The more rigid prices are, the less inflation falls after a decline in output. But why are prices rigid? One answer is the widespread presence of customer markets, the observation that firms accumulate sticky customer bases by selling more output because customers prefer to buy from the same firm over time.[1] Customer markets create rigidity in *real* prices by making markups more countercyclical, especially during financially driven recessions.[2] But how strong is the effect of the customer-market incentive on real price rigidity, and which firm characteristics strengthen this incentive?

This paper argues that investment irreversibility in tangible capital leads to greater real price rigidity because it strengthens the customer-market incentive. Irreversibility amplifies losses from bad idiosyncratic demand shocks in the future, and predictable demand from a sticky customer base insures firms against these losses. To invest in a larger *future* base, firms with more irreversible capital forgo current profits to sell more output *today*. However, if financial constraints tighten and make current profits more valuable, firms with more irreversible capital scale back today's customer investment more sharply, which creates more upward pressure on today's prices and markups. Consistent with this mechanism, I empirically show that firm-specific cuts in credit supply cause prices to fall by less in industries with higher irreversibility. This result is surprising because, under the standard "ex post" intuition, a firm that avoids selling capital due to irreversibility should absorb a cut in credit

[1] See Phelps and Winter (1970), Bils (1989), Gottfries (1991), Rotemberg and Woodford (1993), Ravn et al. (2006), and Nakamura and Steinsson (2011) for theoretical work on customer markets and real price rigidity. Chevalier and Scharfstein (1996), Foster et al. (2016), Gilchrist et al. (2017), Paciello et al. (2019), Renkin and Züllig (2024), and Bauer et al. (2026) find empirical support for customer markets across many industries. Gourio and Rudanko (2014), Peters and Taylor (2017), Chiavari (2026), and He et al. (2026) show that firms also invest in their customer base through selling expenses.

[2] There is empirical evidence that markups are countercyclical, although recent research is mixed. Bils et al. (2018) argues for countercyclical markups while Nekarda and Ramey (2020) finds evidence in favor of procyclical or acyclical markups. Blampied and Mahadeo (2025) provides one reconciliation by showing markups after monetary policy shocks are countercyclical in recessions and procyclical in expansions.

supply by adjusting its price by more, not by less. The estimates imply a quantitatively meaningful increase in real price rigidity in industries with more irreversible capital.

I formalize the mechanism in a two-period partial equilibrium model. I adapt a standard model of customer markets from Ravn et al. (2006) to a two-period setting with partially irreversible investment and uninsurable idiosyncratic demand risk. Irreversibility penalizes the firm when it sells capital after a bad demand shock in the future (second period). A sticky customer base mitigates this problem because demand from the customer base is predictable and unaffected by the demand shock, so a larger customer base functions like precautionary saving. In other words, a larger base lowers a firm's demand risk, which reduces future capital sales after bad shocks and the related losses due to irreversibility. Therefore, firms with more irreversible capital sell more output today (first period) to accumulate larger customer bases as insurance against bad demand shocks in the future.

This stronger customer-market incentive creates more upward pressure on the price and markup response to tighter financial constraints. In a customer market, firms acquire their marginal customer by forgoing current profits, so firms with more irreversible capital forgo more current profits on the marginal customer. Hence, when tighter financial constraints increase the marginal value of liquidity today, firms with more irreversible capital cut back more sharply on their *customer* investment. This behavior creates more upward pressure on prices and markups for firms with more irreversible capital: when prices rise, they rise by more, and when prices fall, they fall by *less*. The key prediction is about the relative response of prices when irreversibility is higher, not the sign. Motivated by empirical evidence from Kim (2021) and Lenzu et al. (accepted) that firms may deal with cuts in credit supply by cutting prices to fire sell inventories, I extend the baseline model to include inventory accumulation. In this extension, prices can fall after financial constraints tighten, but they fall by less when capital is more irreversible. This partial-equilibrium mechanism should increase real price rigidity in general equilibrium during financially driven recessions.

To test this mechanism, I compare the response of product-level prices to firm-specific credit supply shocks in high- versus low-irreversibility industries. Following Chodorow-Reich (2014) and Kim (2021), I construct a shift-share instrument that uses the bankruptcy of Lehman Brothers as a source of plausibly exogenous variation in the credit supplied to firms. This instrument identifies the causal effect of a credit supply shock on prices, and the comparison across industries shows how the response varies with irreversibility, not the causal effect of irreversibility itself. I combine these credit supply shocks with confidential product-level prices from the Producer Price Index (PPI) of the U.S. Bureau of Labor Statistics (BLS), Census Bureau microdata on export prices and markups, and industry-level estimates of physical irreversibility in tangible capital from Kermani and Ma (2023).

One year after the Lehman bankruptcy, an idiosyncratic cut in credit supply by one standard deviation causes firms in low-irreversibility industries to cut prices by 10% while firms in high-irreversibility industries do not cut prices. This difference in behavior is surprising because the standard "ex post" intuition is that irreversibility amplifies other margins of adjustment after a credit supply shock since firms want to limit capital sales. If a firm with low irreversibility cuts prices, then a firm with high irreversibility should cut prices by *more*, not *less*. However, this behavior is consistent with my model's "ex ante" mechanism. Prices fall by less after cuts in credit supply because tighter financial constraints make firms care more about liquidity today and less about insurance against future losses. As a result, firms with more irreversible capital cut back their customer investment more sharply.

Additional evidence points to a stronger ex ante customer-market incentive in industries with higher irreversibility. I obtain similar results using export prices from the Longitudinal Firm Trade Transactions Database (LFTTD), even when I compare the price responses for products with similar demand elasticities. Thus, the result replicates in a distinct dataset, and irreversibility does not seem to be just a proxy for inelastic demand. Among goods with low demand elasticities, exporters in more irreversible industries even increase prices, so firms

in more irreversible industries are not merely insulated from credit supply shocks. Consistent with a difference in customer-market incentives, firms in high-irreversibility industries also temporarily raise markups relative to firms in low-irreversibility industries. Finally, descriptive evidence is consistent with greater ex ante investment in more predictable demand. In industries with higher irreversibility, firm-to-firm contracts are longer, and selling expenses account for a larger share of sales.

The estimated difference in price responses across industries is large enough to change the amount by which aggregate prices fall after a credit contraction. I consider a back-of-the-envelope partial-equilibrium exercise that compares two counterfactuals. One counterfactual scenario supposes that prices in all industries respond to credit contractions like prices in the least irreversible industry. In this scenario, credit contractions alone would have caused prices to fall by almost 12% one year after the bankruptcy of Lehman Brothers. For comparison, the PPI actually fell by 19% over this period.[3] The other counterfactual instead applies the estimated price response for each industry, so prices in high-irreversibility industries fall by less. In this scenario, credit contractions would have caused the PPI to fall by almost 40% less. Thus, the regression estimates imply a quantitatively meaningful effect from irreversibility on real price rigidity after credit contractions.

To check the role of indirect general equilibrium effects, I build a two-industry DSGE calibrated to the regression estimates. I model a steady-state difference in customer-market incentives across industries in *reduced form* rather than explicitly microfounding it as the result of irreversibility. This choice simplifies the analysis and preserves the interaction between indirect effects and the customer-market incentive, which is the important characteristic for the inflation response to credit supply shocks.[4] In the DSGE, since aggregate

[3]The large magnitude of the PPI decline does not contradict the missing deflation puzzle (e.g. Hall 2011, Ball and Mazumder 2011) because the puzzle is about consumer price inflation.

[4]The key assumption is that an aggregate credit supply shock does not cause firms to substantially re-optimize their ex ante demand for customer investment in a way that eliminates the difference in the strength of the customer-market incentive across industries. This assumption is reasonable because the source of the

inflation falls by more when all prices respond as they do in the least irreversible industry, a central bank following a standard Taylor rule cuts the real interest rate by more, and this behavior attenuates the difference in the inflation response to an aggregate credit supply shock by about one half.

Related Literature. This paper's primary contribution is that investment irreversibility in tangible capital leads to greater real price rigidity because it strengthens the customer-market incentive. To the best of my knowledge, this paper is the first to connect two separate strands of the literature, irreversibility and customer markets, to understand how prices behave, especially during financially driven recessions.

This connection points to irreversible capital—and characteristics of the production technology more broadly—as a novel reason why the literature has found that tighter financial constraints increase prices in some settings and decrease them in others. Gottfries (1991), Chevalier and Scharfstein (1996), Gilchrist et al. (2017), Christiano et al. (2015), and Dou and Ji (2021) show that tighter financial constraints create upward pressure on prices due to customer markets and working capital constraints. Renkin and Züllig (2024), Kim and Park (2025), and Bauducco et al. (2026) use plausibly exogenous variation in credit supply to provide empirical support for these channels. However, Kim (2021) and Lenzu et al. (accepted) also use plausibly exogenous variation in credit supply and find that prices tend to *fall*, not rise, due to fire sales of inventories. To explain the difference in signs, Renkin and Züllig (2024) shows that firms in their sample sell goods with low demand elasticities and do not have significant inventory holdings. My results suggest that investment irreversibility also generates upward pressure on price responses alongside demand-side characteristics and inventory holdings. More broadly, the results relate to research showing that financial frictions make the slope of the Phillips Curve state-dependent, such as Acharya et al. (2026),

ex ante demand is idiosyncratic uncertainty, which is far larger than aggregate uncertainty for most firms.

Drechsler et al. (2026), and Liu (2026).

This paper provides a customer-market explanation for why irreversibility is associated with greater price rigidity. Kermani and Ma (2023) shows that irreversibility is correlated with more rigid nominal prices and explains this empirical result with Woodford (2005)'s and Altig et al. (2011)'s theoretical finding that firm-specific capital makes prices strategic complements.[5] In those papers, firm-specific capital means that firms cannot adjust their stock of capital used in current production and must directly invest to adjust their future stock, in contrast to the standard assumption that firms can rent arbitrary amounts of capital for current production from a perfectly competitive market. This paper interprets Kermani and Ma (2023)'s measure of irreversibility as a measure of costly resale rather than of the inability to rent capital for current production. Under this interpretation, this paper provides evidence that the ex ante interaction between irreversibility and the customer-market incentive also explains the correlation between irreversibility and price rigidity. Section 4.4 discusses the distinction between firm-specific capital and costly resale in more detail.

An ex ante interaction between the customer-market incentive and irreversibility also helps explain why customer capital matters even in industries that are not typically associated with consumer brands or product differentiation. He et al. (2026) finds that many business-facing industries spend substantial amounts on selling expenses like salespeople and marketing. According to Foster et al. (2016), markets for homogeneous products like concrete and industrial gases involve demand accumulation through higher sales. In these industries, demand-side returns to a larger customer base are not as obvious as in, for example, consumer or differentiated markets. This paper points out that customer investment in business-facing or homogeneous-product industries could be explained by production technology characteristics like irreversible capital. Other technological characteristics could include operating

[5]Strategic complementarity is a real price rigidity. With small menu costs, a real price rigidity can lead to less frequent price adjustment, which is Kermani and Ma (2023)'s measure of price rigidity. Aruoba et al. (2024) confirms this intuition in a quantitative model.

leverage (see Carlson et al. 2004 and Novy-Marx 2011) and labor irreversibility (see Ghaly et al. 2017, Donangelo et al. 2019, Jäger et al. 2024, and Meeuwis et al. 2025) since these characteristics would also amplify the cost of bad demand shocks.

Outline. Section 2 explains the theoretical mechanism. Section 3 describes the data, empirical methodology, and interpretation of the irreversibility measure. Section 4 presents the price and markup results as well as checks of alternative explanations. Finally, Section 5 uses a back-of-the-envelope exercise to quantify the effect of the ex ante interaction between investment irreversibility and the customer-market incentive on real price rigidity.[6]

2 Irreversibility and Customer Markets

This section presents a stylized two-period partial equilibrium model in which firms face partially irreversible investment and uninsurable demand risk. Because irreversibility amplifies the cost of bad demand shocks in the future, firms have a stronger *ex ante* customer-market incentive since a larger customer base insures against future low demand. However, when tighter financial constraints cause firms to value current profits more relative to future profits, firms with more irreversible capital scale back their customer investment more sharply. This stronger reaction creates more upward pressure on prices and markups. Critically, this reaction occurs in the first period *before* demand uncertainty resolves. Omitted derivations are in Appendix D.

2.1 Setup

There are two periods $t \in \{0, 1\}$. In $t = 0$, the firm produces, and in $t = 1$, the firm's decision is split into the "morning" and the "afternoon." In the morning, the firm learns

[6]This paper contains the main appendix while the supplementary appendix is available on my personal website.

what demand will be in the afternoon and adjusts its capital stock. Denote the demand state by $z \in \{B, G\}$: demand will either be bad or good with equal probability. In the afternoon, the firm produces.

The demand state z represents *idiosyncratic* demand risk, not *aggregate* demand risk. Most firms likely consider idiosyncratic risk, rather than aggregate risk, to be the primary source of concern when it comes to the costs of investment irreversibility because micro uncertainty is far larger than macro uncertainty for most firms. I assume this risk is uninsurable with financial assets, so the customer base will be the only way to insure against low demand.

Production and Investment. The firm produces output using capital and labor according to a Cobb-Douglas production function with constant returns to scale and weight α on capital. Labor is paid an exogenous wage w, and the marginal cost of production is the wage divided by the marginal product of labor. The firm arrives in $t = 0$ with a capital stock of k_0, and capital chosen in the morning of $t = 1$ is given by $k_1^z = (1 - \delta)k_0 + i_1^z$, where the z superscript indicates that i_1^z is chosen conditional on knowledge of the demand state z. Investment is partially irreversible: the firm pays i_1^z when it invests ($i_1^z \geq 0$) but recovers only $(1 - \kappa)i_1^z$ when it disinvests ($i_1^z < 0$), where $\kappa \in (0, 1)$ indexes the degree of irreversibility.

Interpret κ as irreversibility due to the characteristics of a firm's production technology as opposed to the firm's product-market characteristics. For example, κ should arise from mobility costs, not from holdup problems.[7] The wedge κ can be a reduced-form parameter for the remaining amount of irreversibility after a firm adjusts its capital structure, such as holding more cash or arranging for extra credit lines.

[7] Williamson (1989) explains how a firm's capital can become irreversible when it has to be customized or otherwise made specific for a downstream buyer, which creates a holdup problem. Irreversibility is an endogenous outcome of the firm's product market (few potential trading partners) rather than an exogenous characteristic of the production technology.

Customer Demand. In both periods, the firm faces a demand curve with intratemporal elasticity of demand $\eta > 1$. However, the amount of demand at a given price is not the same across time. Specifically, the firm sells output y_t at a price p_t according to

$$y_0 = p_0^{-\eta}, \quad y_1^z = \underbrace{(p_1^z)^{-\eta} z}_{\text{searchers}} + \underbrace{(p_1^z)^{-\eta} \chi y_0^{\theta(1-\eta)}}_{\substack{\text{sticky} \\ \text{customer base}}}, \quad \theta(1-\eta) \in [0, 1). \tag{1}$$

In $t = 1$, the firm gets demand from two types of customers: searchers and a sticky customer base. Demand from searchers is uncertain, but demand from the customer base is predictable.[8] The functional form for demand from the customer base comes from (relative) goods-specific habits as in Ravn et al. (2006), which is a standard way to tractably model customer markets. The parameters $\chi \geq 0$ and $\theta \leq 0$ determine how much an extra sale in $t = 0$ shifts future demand.

Why is there demand uncertainty from searchers? A literal interpretation is that the searchers are customers who do not develop habits, so taste shocks, search frictions, or exogenous churn create uncertainty about demand from searchers. For example, households could derive utility from two baskets of goods. Goods-specific habits apply to one basket, and taste shocks apply to the other basket. The demand curve in (1) could also be a metaphor or simplification of long-term contracts. Searchers represent spot-market buyers whose demand is unknown because they did not sign a contract, and the sticky customer base consists of customers who signed long-term contracts. To acquire customers into long-term contracts, the firm needs to set lower prices in $t = 0$.

[8] According to empirical evidence from Larkin (2013) and Baker et al. (2023), firms with larger or stickier bases have lower future cash flow volatility and are less exposed to negative shocks, consistent with the assumption that demand from a sticky customer base insulates a firm from demand risk.

Objective of the Firm. The firm maximizes the objective

$$\varphi d_0 + \frac{1}{R}\mathbb{E}[d_1^z], \tag{2}$$

where d_t are dividends, φ represents the marginal value of internal liquidity in $t = 0$, and R is the gross risk-free interest rate. It is standard to approximate tighter financial constraints as an increase in φ since tighter constraints in many specifications result in a higher φ. A one percent increase in φ can be interpreted as a one percent increase in the required return on an investment because the firm now values $t = 0$ profits more, and any investment must yield a higher return to be worth the opportunity cost.

Discussion of Model Ingredients. I have designed this model's ingredients to make two points: (i) irreversibility strengthens the customer-market incentive to sell more output today, and (ii) greater irreversibility leads to upward pressure on the price response to tighter financial constraints today. I intentionally put the costs of irreversibility into the future rather than today because this model is about how the *anticipation* of bad future demand shocks leads to an *ex ante* insurance motive to invest in the customer base. Because of this ex ante motive, a firm with greater irreversibility adjusts its price by more when financial constraints tighten in the present, before any idiosyncratic demand uncertainty has resolved. This model is not about how irreversibility affects a firm's decisions *ex post* after a bad shock occurs.

This model focuses on the ability of the customer base to insure against low demand and purposefully ignores other options. Notably, I do not allow the firm to adjust its capital stock in $t = 0$. Shutting off investment in $t = 0$ allows for a sharper statement of the interaction between irreversibility and the customer-market incentive. If I did allow investment in $t = 0$, then an increase in the irreversibility wedge κ would not only increase the cost of selling capital in the future but also likely cause the firm to scale down the entire operation in $t = 0$

because the user cost of capital increases with κ. In reality, however, a higher κ would likely reflect a difference in the type of capital used, and the price of this capital could then adjust so that the expected return on the firm's capital offsets the higher user cost. We could also imagine that the initial period $t = 0$ represents normal times during which a firm does not want to make any adjustment to its capital stock due to large fixed costs. For these reasons, it is a reasonable assumption to only allow the capital stock to adjust in $t = 1$.

Another key assumption is the additive form of the $t = 1$ demand curve (1). An alternative choice would be a multiplicative form, where demand from *all customers* is uncertain. The customer base then just shifts the expected volume of demand. I do not take this alternative approach because it does not capture the common notion that the customer base leads to predictable demand.[9] Under multiplicative demand shocks, while the expected return on capital still rises with a larger customer base, exposure to the idiosyncratic demand shock also rises so that a bad demand shock is larger in magnitude. In contrast, when I use the additive form, exposure to the demand shock falls with a larger customer base, which better fits the idea that customer bases provide predictable demand.

Connection to Price Rigidity. This model has a *real* price rigidity, not a nominal rigidity. At the firm level, prices are not literally rigid. However, there is upward pressure on the price and markup responses when tighter financial constraints increase φ, the marginal value of liquidity. This incentive makes markups more countercyclical in general equilibrium because adverse shocks usually tighten financial constraints and push markups higher. This upward pressure on markups offsets the usual downward pressure on marginal costs that causes inflation to fall after declines in output. See Ravn et al. (2006) and Gilchrist et al. (2017) for how customer markets make aggregate prices more rigid in general equilibrium

[9] Dou et al. (2021) models the customer base as deterministic in an environment with liquidity shocks. Using household transactions data, Baker et al. (2023) finds that firms with less customer churn experience a smaller decline in demand in downturns, consistent with the idea that a sticky customer base insulates against demand risk.

through countercyclical markups, especially during financially driven recessions.

2.2 The Price Response to Tighter Financial Constraints

This section characterizes the elasticity of prices in $t = 0$ to φ, the marginal value of liquidity. First, I study the price response when customer markets are shut off. Second, I study the price response when customer markets are turned on. Third, I study why irreversibility affects the price response by strengthening the customer-market incentive. Fourth, I explain that the model's key prediction is about the relative magnitude of the price response to a shift in φ and not the sign.

No Customer Markets. Without customer markets, the firm sets the price in each period equal to a constant markup over the marginal cost. Because an increase in φ has no effect on the marginal cost in $t = 0$,[10] the firm actually does not respond at all. The firm's choice of production is purely static, so it already maximizes profits from labor in $t = 0$, and the firm has no other way to increase dividends. Further, the size of the irreversibility wedge κ has no effect on the firm's price choice in $t = 0$.

Adding Customer Markets. With customer markets, the firm chooses the price

$$p_0 = \frac{\eta}{\eta - 1}\left(\underbrace{mc_0}_{\text{marginal cost}} - \underbrace{\frac{\lambda}{\varphi}}_{\substack{\text{customer-market} \\ \text{incentive}}} \right), \quad \lambda = \frac{1}{R}\mathbb{E}\left[\frac{\partial d_1}{\partial y_0}\right]. \tag{3}$$

The firm's price in $t = 0$ equals the standard monopolist's markup over the difference of two terms: the marginal cost and the customer-market incentive. Because a sale in $t = 0$ not only generates revenue but also brings future demand in the afternoon of $t = 1$, a firm

[10] The marginal cost comes from hiring more labor. An earnings-based or collateral-based constraint would generally imply no effect on the cost of another hour of labor input, but a working capital constraint on the wage bill would.

has an incentive to cut its price, even though a lower price causes the marginal sale to strictly reduce the firm's profits in $t = 0$. The strength of this customer-market incentive to cut the price depends on how much the marginal sale improves future expected dividends after discounting by the marginal value of liquidity φ and the gross interest rate R. In this model, the firm adjusts its price after a shift in φ as follows:

Proposition 2.1. *The firm increases its log price and log markup in* $t = 0$ *with* $\log \varphi$*:*

$$\frac{\partial \log p_0}{\partial \log \varphi} > 0 \text{ and } \frac{\partial \log \mu_0}{\partial \log \varphi} > 0. \tag{4}$$

This proposition is in line with models of customer markets and financial constraints in previous research (see Gottfries 1991, Chevalier and Scharfstein 1996, and Gilchrist et al. 2017), and it is not the primary contribution of this paper. The primary contribution is a novel mechanism that links irreversibility to price rigidity through the customer-market incentive.

Another intuition for why prices rise is that the customer-market incentive makes the firm behave as though it faces a more elastic demand curve in the long run than in the short run. In this model, the short-run elasticity is $-\partial \log y_0 / \partial \log p_0 = \eta > 1$, so lower prices lead to more output sold.[11] However, the firm's price p_0 affects not only current output sold y_0 but also future output sold y_1, so the firm sets p_0 based on the present value of output sold, not just the current period's value. Thus, the firm behaves as if p_0 has a bigger effect on y_0 than it actually does. In other words, the long-run demand elasticity is higher than the short-run elasticity. An increase in the marginal value of liquidity φ reduces the present value of future output sold and makes the firm behave as if its long-run demand elasticity has fallen, which pushes p_0 up, just like a markup shock to η.

[11] This result holds because I assume customers have *relative* deep habits as opposed to *additive* deep habits. In the latter specification, the short-run elasticity becomes endogenous with the level of output sold. See Ravn et al. (2006) and Binsbergen (2016).

The optimality condition for the firm's price in the afternoon of $t = 1$ remains the same as the model without customer markets because the firm has no incentive to accumulate a customer base in $t = 1$. The level of the firm's price may not be the same because the total amount of demand in $t = 1$ influences the price through the marginal cost, but the firm's markup over marginal cost is just $\frac{\eta}{\eta-1}$.

Higher Irreversibility Strengthens the Customer-Market Incentive. Proposition 2.2 states this model's key result:

Proposition 2.2. *Assume the demand states B and G are sufficiently far from each other, the irreversibility wedge κ is sufficiently small, and χ is not too large relative to k_0, so that the firm disinvests in the morning of the $t = 1$ bad state ($i_1^B < 0$) and invests in the morning of the $t = 1$ good state ($i_1^G \geq 0$). Then a firm with higher irreversibility*

(i) invests more in the customer base, $\dfrac{\partial \log y_0}{\partial \kappa} > 0$, and

(ii) has a higher elasticity of prices and markups to shifts in φ:

$$\frac{\partial^2 \log p_0}{\partial \kappa \, \partial \log \varphi} > 0 \text{ and } \frac{\partial^2 \log \mu_0}{\partial \kappa \, \partial \log \varphi} > 0. \tag{5}$$

The assumptions of this proposition ensure the analysis is not moot. If B is not sufficiently low, then the firm may not sell capital, in which case κ is irrelevant. If G is not high enough, then the good state is not really a good state. If κ is too high, then the firm may simply not sell any capital when $z = B$, in which case a marginal increase in κ has no effect on outcomes. Finally, χ parameterizes the impact of y_0 on the future customer base in the afternoon of $t = 1$. If it is too large relative to the firm's initial capital stock k_0, then the firm may not sell any capital when $z = B$. The mathematically precise statements of these assumptions are provided in Supplementary Appendix S5.1.

The intuition for Proposition 2.2(i) is that higher irreversibility raises the cost of each capital sale when demand is low, and a larger customer base reduces how much capital is sold by dampening the fall in demand. The following two derivatives illustrate why the firm considers a larger irreversibility wedge κ to be painful. Holding y_0 constant,

$$\frac{\partial d_1^B}{\partial \kappa} = i_1^B < 0, \quad \frac{\partial d_1^G}{\partial \kappa} = 0.$$

These two derivatives show how κ affects future dividends if the firm cannot adjust its sales in $t = 0$. A small increase in κ reduces the firm's dividends in the bad state in proportion to the units of capital already being sold but has no effect on d_1^G because the firm does not sell capital in that state. If we treat y_0 as a parameter instead of an optimal choice and differentiate with respect to it, then we obtain

$$\frac{\partial^2 d_1^B}{\partial y_0 \, \partial \kappa} = \frac{\partial i_1^B}{\partial y_0} \propto \frac{\partial (B + \chi y_0^{\theta(1-\eta)})}{\partial y_0} > 0, \quad \frac{\partial^2 d_1^G}{\partial y_0 \, \partial \kappa} = 0.$$

The first mixed derivative shows that an increase in κ reduces d_1^B by less because higher output sales y_0 cut how much capital the firm sells in the morning of $t = 1$. The reason the firm sells less capital is that a higher y_0 leads to a higher level of demand in the afternoon of $t = 1$. The marginal unit of capital is now worth keeping instead of selling. Since the customer-market incentive λ/φ is just the present discounted expected effect of y_0 on future dividends, the customer-market incentive λ increases with κ and leads to higher output sales in $t = 0$.[12]

Proposition 2.2 shows that higher irreversibility strengthens the customer-market incentive, and as a result, the sensitivity of prices to shifts in liquidity demand increases. When

[12]Higher sales in $t = 0$ mean the firm sets a lower price and thus a lower markup in $t = 0$. Empirically, markups seem to increase with the size of a customer base (see Baker et al. 2023). An alternative demand curve like in Binsbergen (2016) would allow the demand elasticity to fall with the size of the customer base, which would generate higher markups. The results in this model should still go through as long as a firm still has an incentive to make more sales in $t = 0$ to accumulate the customer base.

the irreversibility wedge κ increases, the firm forgoes profits in $t = 0$ to obtain a larger customer base in $t = 1$ if demand from searchers is low. But if the firm needs liquidity in $t = 0$ because φ rises, then the firm cuts back on sales and hikes prices much more aggressively than a firm with lower irreversibility. The intuition is that, for small κ, the firm only loses a little money on the marginal customer because marginal revenue is still close to marginal cost, while, for high κ, the firm accepts a very large loss to make one more sale. Thus, a one percent cut in output sold reduces the firm's marginal loss by a smaller percentage when κ is high. When the marginal value of liquidity in $t = 0$ rises, a firm with more irreversible capital needs to cut back on output sold more sharply to reduce its marginal loss by one percent than a firm with less irreversible capital.

Relative Magnitudes, Not the Sign. The key prediction of this model is that higher irreversibility increases the elasticity of prices to the marginal value of liquidity φ, not that prices rise. In the baseline model with only customer markets, the elasticity is always positive. The elasticity can be negative, however, once the firm has a price-cutting lever to raise liquidity. Motivated by Kim (2021), Lenzu et al. (accepted), and my own empirical evidence, I introduce inventories into the model as a way for the firm to raise liquidity while cutting prices. Appendix E shows that even if the elasticity of prices to φ is negative, a higher irreversibility wedge κ still increases the elasticity. In other words, a firm optimally cuts its price after a rise in $t = 0$ liquidity demand, and a firm with higher irreversibility cuts by less.[13]

The intuition behind this result is that the customer base and inventory stock are two assets from which the firm disinvests after a rise in φ, and the price response depends on whether the firm ultimately cuts or hikes the amount of output sold. With inventories, there is a distinction between output *produced* and output *sold*. A firm can simultaneously cut

[13] I also show that the markup result remains true under an additional *sufficient* condition that the marginal benefit to customer acquisition is sufficiently strong.

output produced and increase output sold, which pushes prices down, if the firm accumulates fewer inventories. However, since inventories do not reduce demand risk the way that a sticky customer base does, greater irreversibility still strengthens the customer-market incentive. As a result, a firm with greater irreversibility will cut back relatively more on its production, which can lead to an elasticity of price p_0 to φ that is negative and increases with the irreversibility wedge κ.

3 Data and Empirical Methodology

This section describes how I will provide empirical support for the theory in Section 2. I first describe my datasets followed by the construction of the credit supply shock, the main regression specification, and the identification assumptions.

3.1 Data Sources

Description. I construct a novel dataset, which I call the PPI-Census-Dealscan dataset, using (i) confidential item-level price data underlying the Producer Price Index (PPI) published by the Bureau of Labor Statistics (BLS),[14] (ii) bank lending information from Dealscan, (iii) estimates of investment irreversibility by industry from Kermani and Ma (2023), (iv) balance-sheet information from Mergent FISD, Compustat, and the Quarterly Financial Report in Economic Census Years (QFRCEN), and (v) other confidential microdata from the Census Bureau. See Supplementary Appendix S1.1 for details on how I clean and construct this dataset.

The BLS constructs the PPI through monthly surveys of about 100,000 items from approximately 25,000 establishments across many industries, including services. Price quotes are based on transactions and adjusted for quality changes or product substitutions so that

[14] My access to the PPI microdata was indefinitely suspended as of September 2025 due to limited resources at the BLS to support external research projects.

true price changes are measured. Items are uniquely identified by price-determining characteristics, such as the type of buyer, color, and size. The BLS samples establishments to be representative of the entire U.S. production sector, and items are randomly sampled from all the items produced by a given establishment. See U.S. Bureau of Labor Statistics (2014a) and U.S. Bureau of Labor Statistics (2014b) for more details on the survey methodology and quality adjustment procedures, respectively.

I use Dealscan to measure bank lending to firms. This database provides comprehensive historical information on large syndicated loans at issuance and after amendments. In this market, a group of banks comes together as a syndicate to issue a loan. One or more banks work as the "lead arranger," which drafts the loan agreement, performs due diligence, and recruits participants. Typically, the lead arranger retains a large share of the loan.[15] While Dealscan does not cover all bank loans, Chodorow-Reich (2014) shows that it comprises nearly half of all commercial and industrial bank loans and two-thirds of lending with a maturity greater than 1 year.

My analysis proxies investment irreversibility at the industry level as one minus the predicted industry-average recovery rate of PPE based on physical attributes.[16] This measure comes from Kermani and Ma (2023), which estimates the recovery rate on property, plant, and equipment (PPE) by 2-digit SIC industry using data from Chapter 11 bankruptcy filings. The authors show that Chapter 11 filings require an orderly liquidation analysis (OLA). An

[15]Using confidential microdata from the Shared National Credit Registry (SNC), Blickle et al. (2022) shows that the lead arranger does not always retain a large share because the arranger often sells a portion of its stake after loan issuance. As a result, the raw Dealscan data may overstate the loans issued by lead arrangers. My analysis, however, uses code provided by Blickle et al. (2022) that predicts the actual stake retained by each participant in a syndicated loan.

[16]This paper focuses exclusively on the irreversibility of *tangible* capital and does not consider *intangible* capital. The primary reason is measurement: I argue Kermani and Ma (2023) provides a credible measure of irreversibility for tangible capital, but there is no similar measure for the irreversibility of intangible capital. Further, such a measure would also need to exclude the role of *customer capital* since investment in future demand is itself a form of intangible capital. Nevertheless, in principle, firms with more irreversible intangible capital, such as intellectual property or organizational capital, should also want stickier customers to deal with demand uncertainty.

orderly liquidation differs from a forced liquidation or fire sale because the firm would get 6–12 months to liquidate, which mitigates the size of fire sale losses. The key object from an OLA is the expected recovery rate for PPE as a fraction of the PPE's book value. This rate can be interpreted as a measure of the irreversibility wedge κ from Section 2 because one minus the recovery rate is precisely the fraction of value that would be lost when the firm sells tangible capital. In Section 3.4, I discuss in more detail why I use the *predicted* recovery rates to measure irreversibility. A 10pp increase in my measure of irreversibility means that a firm expects to get 10pp less as a share of the book value of its tangible capital.

Several of the tests in Kermani and Ma (2023) support this interpretation of the recovery rate as a measure of investment irreversibility for tangible capital. Differences in the average recovery rate across industries can be explained by industry-level differences in the physical attributes of the capital used.[17] Firms in industries with lower recovery rates sell capital less frequently and cut investment rates by more after an increase in uncertainty, which is consistent with a stronger real options channel due to higher irreversibility. These two results also assuage the concern that recovery rates only predict behavior during bankruptcy and not during normal times.

I supplement the previous data sources with firm financial information and additional microdata from the Census Bureau. Mergent FISD provides information about previous bond issuance. For some regressions, I add balance-sheet controls like book leverage using data from Compustat and the QFRCEN, and I control for firm age and employment size using the Longitudinal Business Database (LBD). I also study the behavior of export prices, markups, inventories, and capital stocks with data from the Longitudinal Firm Trade Transactions

[17] They consider four attributes: mobility, customizability, durability, and the share of structures in capital. Mobility is measured as transportation costs of capital equipment from producers to users divided by production costs incurred by the industries which produced the equipment. Customizability is measured as design costs incurred by equipment producers divided by production costs. Durability is measured using an industry's depreciation rates from Compustat. Structure shares are measured from the BEA detailed fixed asset tables.

Database (LFTTD) and Annual Survey/Census of Manufactures (ASM/CMF).

Although the PPI-Census-Dealscan dataset has shortcomings, it has unique advantages that make my empirical design feasible. Critically, I need price data from firms that face idiosyncratic credit supply shocks and heterogeneity in irreversibility. Because my irreversibility measure is at the industry level, ACNielsen scanner price data in Kim (2021) is not usable since it primarily covers the food and beverage industry whereas the PPI covers many more industries. Samples from other countries may be larger in size due to better collection of price and quantity data, but to the best of my knowledge, other countries do not have cross-industry data on irreversibility.

Sample Characteristics. Table B.1 summarizes key characteristics of the main sample. The main sample consists of approximately 350 firms that appear in both the PPI and Dealscan. Most of the firms are public, over half are manufacturers, and over half have issued bonds. Firms in my sample are mostly large employers and old. The mean value of irreversibility is 63% and from 57% at the 10th percentile to 71% at the 90th percentile. The table also summarizes the credit supply shock and Lehman exposure IV, which are defined in Section 3.2. The distributions of these two variables are similar to Kim (2021)'s sample, which only includes producers of consumer packaged goods, so these measures of credit supply are not driven by the industries of the borrowers. Finally, I find that the correlation in monthly inflation rates over 2007:Q3–2009:Q3 between the aggregate price index implied by my sample and the aggregate price index implied by the entire PPI microdata is about 0.59.[18] This moderately high correlation suggests that the pricing behavior in my sample is fairly similar to the broader economy's.

[18]The small sample size limits the number of estimates that I could disclose, so I just report the correlation instead of plotting the time series for both indices.

3.2 The Credit Supply Shock and Regression Specification

This section explains why I choose credit supply shocks to provide empirical support for the theory in Section 2, how I measure credit supply shocks, the regression specification, and the identification assumptions.

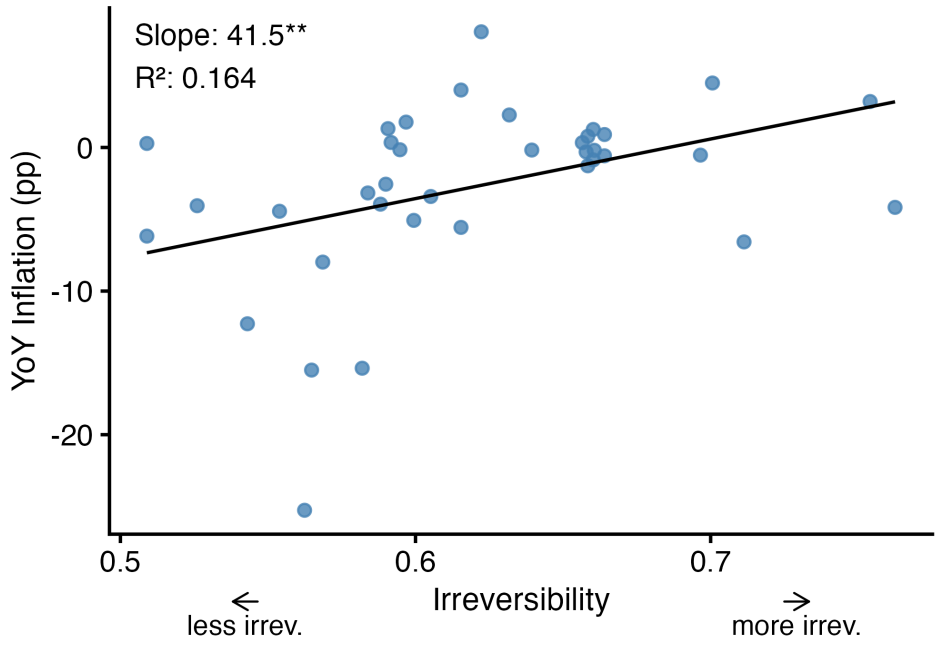
Why Credit Supply Shocks for Empirical Variation? My empirical analysis uses firm-specific credit supply shocks to proxy for shifts in the marginal value of liquidity φ and compares the impact on prices in industries with high irreversibility to the impact in industries with low irreversibility. In principle, other empirical shocks could also test the prediction that higher irreversibility strengthens the customer-market incentive. In my model, an increase in φ is equivalent to an increase in the gross interest rate R. An alternative empirical strategy could be a regression of prices on monetary policy shocks interacted with irreversibility.

This paper uses credit supply shocks over other discount rate shocks like monetary policy shocks because the statistical power of credit supply shocks should be much larger. It is well established (see Ramey 2016, Bauer and Swanson 2022) that many monetary policy shock series involve small shocks. In contrast, credit supply shocks during the Global Financial Crisis were likely both large for a given firm and heterogeneous across firms because some banks were much more exposed to the subprime mortgage crisis.

It is also important to use variation in credit supply across firms within the same industry because a naive comparison of price changes by industry does not provide causal estimates of credit supply shocks on prices. For example, because the bankruptcy of Lehman Brothers reduced credit supply to non-financial firms, we might be tempted to test the theory in Section 2 by plotting industry-level inflation rates after the bankruptcy of Lehman Brothers against irreversibility. Figure 1 shows that this approach is consistent with the theory: industries with high irreversibility tend to have less negative year-over-year inflation

rates across industries at the 3-digit NAICS level. However, industries may experience other shocks like productivity shocks, which confound an interpretation of this figure's price changes as the result of a shift in the marginal value of liquidity φ. For this reason, I turn attention to plausibly exogenous variation in credit supplied to individual firms.

Figure 1: Prices Fall by Less in High-Irreversibility Industries After the Lehman Bankruptcy



Notes: This figure plots the year-over-year inflation in 3-digit NAICS PPI indices over September 2008–2009 against irreversibility from Kermani and Ma (2023). I exclude NAICS 211 (oil & gas extraction) as an outlier since its inflation rate is driven by the collapse in oil prices over 2008–2009.

Definition of the Credit Supply Shock. I measure credit supply shocks caused by the bankruptcy of Lehman Brothers in September 2008 following Chodorow-Reich (2014). The change in bank b's credit supply to firm f from the pre-Lehman period to the post-Lehman period is

$$\Delta L_{f,b} = \frac{\#\text{ loans to all firms except } f,\ \text{Oct. 2008–Jun. 2009}}{\frac{1}{2}(\#\text{ loans Oct. 2005–Jun. 2006} + \#\text{ loans Oct. 2006–Jun. 2007})}. \tag{6}$$

The numerator counts the number of loans lent in the post-Lehman period while the denominator counts the average number of loans over two pre-Lehman periods.[19] A decrease in $\Delta L_{f,b}$ means that bank b has issued relatively fewer loans to firms other than f during the post-Lehman period compared to the pre-Lehman period. If bank b has issued fewer loans to all other firms, then its likelihood to supply loans to firm f has probably fallen, too.

To obtain a firm-level credit supply shock, I aggregate $\Delta L_{f,b}$ across banks in the firm's last loan syndicate. Specifically, let S_f denote the set of banks which comprises the last syndicate for firm f and $s_{f,b,\text{last}}$ the share lent by bank b.[20] Then

$$\Delta L_f = \sum_{b \in S_f} s_{f,b,\text{last}} \, \Delta L_{f,b}. \tag{7}$$

For interpretability of coefficients, I use $\Delta \widetilde{L}_f$, which rescales ΔL_f to unit variance.

My primary analysis instruments the credit supply shock $\Delta \widetilde{L}_f$ because $\Delta \widetilde{L}_f$ may not be plausibly exogenous for reasons that I discuss below in Section 3.3. My instrument is the Lehman co-syndication IV, which is the fraction of a bank's syndication portfolio where Lehman Brothers had a lead role, following Ivashina and Scharfstein (2010) and Chodorow-Reich (2014).[21] An advantage of using an instrument instead of reporting the reduced form is that the credit supply variable $\Delta \widetilde{L}_f$ has more interpretable units than the co-syndication IV. The IV is a shift-share instrument. There is a *single aggregate* shift (the Lehman bankruptcy in September 2008) and firm-specific exposure weights because a firm's lenders may have co-syndicated loans with Lehman. The intuition for why this IV provides exogenous variation in credit supply is that borrowers with credit lines from Lehman could not draw credit from Lehman anymore, so these borrowers precautionarily drew down their credit lines with the

[19] The number of loans issued by a bank b over some time period T is $\sum_{t \in T} s_{f,b,t}$, where $s_{f,b,t}$ is the share of a loan issued to firm f by bank b at time t.

[20] Many loans in Dealscan do not have lender shares. I impute these shares in a two-step procedure. First, I use Blickle et al. (2022)'s method to predict lender shares. Second, if a lender share is still missing, then I impute the lender share based on the syndicate structure following Chodorow-Reich (2014) and Kim (2021).

[21] I thank Gabriel Chodorow-Reich for providing these instruments at the parent bank level on his website.

other banks in their last syndicate. Focusing on syndicated loans in which Lehman was a lead arranger ensures that these drawdowns were significant in size. Therefore, banks that co-syndicated with Lehman more frequently had less capacity to issue loans to non-financial firms because of disruptions in financial markets, not because of shocks to their borrowers.[22] To get a firm-level version of this IV, I compute the weighted average of the co-syndication fractions based on the loan shares from a firm's last pre-crisis loan. Section 3.3 discusses identification assumptions for this instrument in more detail.

Regression Specification. My main regression specification is the unweighted triple difference-in-differences (DiD) regression

$$\begin{aligned}\pi_{g,f,t} = &\sum_{k \in T} \mathbb{1}(t=k)\left[\beta_{0,k}\left(-\Delta\widetilde{L}_f\right) + \beta_{1,k}\left(-\Delta\widetilde{L}_f \times H(\text{Irrev}_{\text{ind}(f)})\right)\right] \\ &+ \sum_{k \in T} \mathbb{1}(t=k)\left[\gamma_{0,k} H(\text{Irrev}_{\text{ind}(f)}) + \gamma_k^\top X_f\right] + \Gamma_{g,t} + \Gamma_{\text{ind}(f),t} + \varepsilon_{g,f,t}\end{aligned} \tag{8}$$

where f is a firm, g is a product group, t is a quarter, $T = \{\text{2007:Q3}, \ldots, \text{2009:Q3}\} \setminus \{\text{2008:Q3}\}$, $H(x)$ is some function, and X_f is a set of firm characteristics measured before the Lehman bankruptcy.[23] This specification estimates the dynamic effect of exposure to the credit supply shock on product-level inflation while allowing the effect to vary across industries with different levels of irreversibility. I include product group by time fixed effects to absorb common shocks to a product group and 3-digit NAICS industry by time fixed effects so that the coefficient $\beta_{0,k}$ is identified using variation among firms within the same 3-digit NAICS industry that experience different credit supply shocks. The coefficient $\beta_{1,k}$ is identified using variation across industries in how a firm responds to the *same* credit supply

[22] In Supplementary Appendix S3.1, I check that the two other instruments used by Chodorow-Reich (2014) yield similar results. I focus on the Lehman co-syndication IV because it has the clearest story for why the exclusion restriction should hold and because disclosure avoidance requirements by the Census Bureau limit the number of estimates I can report.

[23] I define a quarter as the price observation in the first month of the quarter, so the year-over-year change in 2009:Q3 is given by the log change in prices over July 2008–2009.

shock. In my analysis, I use either $H(x) = x$ (linear continuous interaction) or $H(x) = \mathbb{1}(x \geq \text{median})$ (binary indicator for whether a firm has above-median irreversibility). I use the negative of the credit supply shock on the right-hand side so that $\beta_{0,k}$ and $\beta_{1,k}$ describe the impact of a credit *tightening* on price changes. To address potential endogeneity of the credit supply shock, I instrument $-\Delta\widetilde{L}_f$ and $-\Delta\widetilde{L}_f \times H(\text{Irrev}_{\text{ind}(f)})$ with the Lehman co-syndication IV and its interaction with $H(\text{Irrev}_{\text{ind}(f)})$. I justify this strategy in Section 3.3. Because I omit 2008:Q3, $\beta_{0,k}$ and $\beta_{1,k}$ describe the impact *relative* to the price change a firm would have chosen in 2008:Q3. I cluster standard errors by a firm's primary lender since firms which primarily borrow from the same lender likely experience similar treatment effects. Chodorow-Reich (2014) and Lenzu et al. (accepted) also make this choice.[24]

The outcome variable $\pi_{g,f,t}$ denotes the year-over-year inflation rate in quarter t on the price index for a product group g sold by firm f. I choose year-over-year rates to mitigate seasonality and to follow Kim (2021)'s event-study specification. A product group g is a 4-digit NAICS code by buyer type pair. I study pricing dynamics at the product-firm level because the BLS only collects prices for a random sample of the products sold by a firm. To reduce measurement error from random sampling, I do not aggregate product-level prices to a firm-specific price. Items in the PPI microdata are also assigned more granular product codes than 4-digit NAICS, but because of the sample size I need to aggregate. I include the buyer type, which can be "Final User," "Intermediate," or "Same Price to All," since the type of buyer may influence how prices are set.[25] I give details on the construction of $\pi_{g,f,t}$ from item-level prices in Supplementary Appendix S1.1.

The controls X_f account for the dynamic effects of ex ante characteristics on price changes that could otherwise threaten a causal interpretation of the estimated responses

[24] Lenzu et al. (accepted) finds that clustering by primary lender leads to more conservative standard errors than the method proposed by Adão et al. (2019).

[25] Products sold as intermediates may have their prices set according to long-term contracts rather than spot prices. The ability of a firm to adjust its price may be significantly different since these contracts may ex ante constrain how prices can move.

to credit supply shocks. My choice of controls follows Chodorow-Reich (2014) and Kim (2021). The first set of controls accounts for differences in access to external financing. I include fixed effects for previous bond market issuance in Mergent FISD, whether the firm was publicly listed, whether the firm ever had multiple lead arrangers on a loan issued before Lehman's bankruptcy, and the number of loans (partitioned into bins) due over 2008:Q4–2009:Q2. Since lending relationships are sticky, I also use characteristics of the last syndicated loan issued before the Lehman bankruptcy as proxies for a borrower's financing access. Specifically, I include continuous covariates for the interest spread, log size, and maturity of the last syndicated loan and fixed effects for whether the last loan was a credit line or other type (typically a term loan), the year of the last loan, and whether the last loan had multiple lead arrangers. The second set of controls comprises log age and log employment since the firm dynamics literature has found firm age and size to be important predictors of behavior. See Supplementary Appendix S1.1 for more details on these control variables and their construction.

3.3 Identification Assumptions for the Credit Supply Shock

The credit supply shock $\Delta\widetilde{L}_f$ (7) and the Lehman co-syndication IV are relevant under the assumption that borrowers and lenders form sticky relationships. In other words, if firm f's previous lenders reduce the supply of credit to f, then f is not able to easily replace the lost credit with loans from other lenders, so f actually faces a decline in its sources of financing. Lending relationships can be sticky because of asymmetric information or search costs. There is empirical support for this assumption in syndicated loan markets (see Sufi 2007, Chodorow-Reich 2014) and for all commercial and industrial loans issued by the largest U.S. banks (see Amiti et al. 2026).

The coefficients $\beta_{0,k}$ and $\beta_{1,k}$ in (8) can be interpreted as the causal impact of a credit supply shock on price changes relative to the changes chosen in 2008:Q3 for firms in high- or

low-irreversibility industries if the exposure weights implied by the Lehman co-syndication IV are exogenous. Recall that the Lehman IV is a shift-share instrument, and Goldsmith-Pinkham et al. (2020) shows that independence of the weights is sufficient (but not necessary) for shift-share instruments to satisfy exclusion restrictions. I argue this assumption is reasonable for the Lehman IV. The decision by a bank to co-syndicate a loan with Lehman seems entirely unrelated to its decision about the type of borrowers to whom it lends, especially since the Lehman bankruptcy was unexpected. Further, it seems implausible that some firm types which happen to change prices differently than other types also systematically prefer to borrow from banks that co-syndicate frequently with Lehman. In other words, this instrument satisfies the exclusion restriction as long as, conditional on observables, banks which co-syndicated with Lehman more frequently did not systematically lend to different types of firms than other banks. The narrative evidence also supports this assumption. The Lehman bankruptcy was widely viewed as unexpected, so concern about exposure to Lehman likely did not affect which bank-firm pairs signed loans.[26] Lehman went bankrupt due to the mortgage market rather than the commercial and industrial lending market. Thus, it is more likely that loan issuance to firms fell because banks had to cut lending to all non-financial firms than because firms which were adversely affected by housing price declines drew down their existing credit lines so much that banks had to limit lending to most firms.

The credit supply shock $\Delta\widetilde{L}_f$ also functions like a shift-share instrument in that a firm's exposure weights are its last syndicate's loan shares across different banks adjusted by how much lending fell to other firms, but this measure requires stronger assumptions for exogeneity. In particular, when firm f's banks decrease lending to other firms, the cause must be that these banks experienced a credit supply shock. However, this assumption is violated if firm f experiences a shock unrelated to credit supply and heavily draws down its credit lines because then firm f's banks have not, in fact, reduced credit to firm f. Instead,

[26] See Chodorow-Reich (2014) for a detailed narrative account of the Lehman bankruptcy.

firm f's banks have lent less to other firms because they extended substantial credit to firm f. Using the Lehman co-syndication IV as an instrument assuages this concern since it is a plausible credit supply shock.

Finally, I run two more checks that my credit supply shock measures are plausibly exogenous. First, the credit supply shock $\Delta\widetilde{L}_f$ passes the test introduced by Khwaja and Mian (2008). This test checks for selection on unobserved firm characteristics by testing whether a bank that cuts its lending portfolio also cuts lending to firms to whom the bank has previously lent credit. The results are reported in Appendix B.2. Second, I regress observable firm characteristics on the Lehman co-syndication instrument.[27] The results are reported in Appendix B.3. The instrument is not correlated with most characteristics, so it likely reflects changes in bank health rather than firm characteristics.

3.4 Assumptions About the Irreversibility Measure

I measure irreversibility as one minus the *predicted* time-averaged recovery rate of PPE based on physical attributes measured in 1997. This section discusses my assumptions about this measure so that I can interpret the empirical analysis as supporting evidence for this paper's key theoretical argument: irreversibility leads to greater real price rigidity by strengthening the customer-market incentive. First, I argue that my measure of irreversibility can be interpreted as a production technology characteristic. Second, I discuss why my regression (8) does not cleanly estimate the causal effect of irreversibility on the price response to credit supply shocks and how I address this concern.

Irreversibility as a Production Technology Characteristic. This paper interprets the predicted recovery rate of PPE based on its physical attributes from Kermani and Ma

[27] I focus on sample balance with respect to the Lehman co-syndication instrument rather than the credit supply shock because I instrument most regressions. What matters then for a causal interpretation is whether the Lehman instrument systematically affects certain types of borrowers.

(2023) as a *production technology characteristic*. This assumption is necessary because the model's key comparative static is the change in the price response to a shift in the marginal value of liquidity when a firm's production technology is more irreversible, holding constant other features of the firm's problem like the characteristics of the demand curve.[28]

A natural concern is that irreversible industries also differ in their demand-side characteristics, in which case the measure would capture product-market differences rather than production technology. To assuage this concern, Appendix A.1 shows that (one minus) the predicted recovery rate is not strongly associated with several demand-side characteristics that might shape the ability to accumulate customers. Notably, irreversibility is not strongly related to the share of domestic customer demand from households, the share of commodities classified as exchange-traded according to Rauch (1999), or the share of firms with major customers in Compustat Segment.[29] The first fact assuages the concern that irreversible industries invest more in their customer base because they sell more to households, who may have stickier demand due to stronger behavioral frictions. The second fact reduces the possibility that irreversible industries have more gains from investments in buyer relationships because they sell more goods which are not traded on exchanges or because their products are more differentiated. Consistent with this evidence, Foster et al. (2016) finds that the customer-market incentive applies even in industries with relatively homogeneous products like chemicals and ready-mix concrete. The third fact mitigates the issue that irreversible industries may tend to have higher buyer concentration, which would strengthen incentives to invest in buyer relationships and could make capital more irreversible due to holdup problems. In the regression analysis, I also check that price responses differ by industry irreversibility for products with similar demand elasticities.

[28] In Section 2's model, the disinvestment wedge κ must shift, not the customer-market parameters χ and θ or the demand elasticity η.

[29] If a firm has a customer which accounts for more than 10% of the firm's revenue, then Compustat Segment records the firm-customer relationship.

The physical attributes selected by Kermani and Ma (2023) are also plausibly unrelated to the degree of relationship specificity across industries. Capital can be irreversible when it is physically difficult to move. Kermani and Ma (2023) measures this property by an industry's mobility costs using the ratio of equipment transportation costs (from producers to users) to production costs and the share of structures in the capital stock. For example, high mobility costs help explain why the chemicals industry is relatively irreversible among goods producers, whereas the textiles industry is relatively reversible. Equipment in the chemicals industry can be costly to transport because of their size, such as reactors weighing hundreds of metric tons, while looms for textiles reach only a few metric tons.[30] Capital can also be difficult to resell when depreciation makes it less durable because redeploying capital takes time, so quickly depreciating capital will be much less valuable when it is actually redeployed. This reason also helps explain why the chemicals industry is more irreversible than the textiles industry. Equipment for chemicals production is highly susceptible to corrosion from, for example, use of acidic fluids and interaction with moisture in the environment, which continue to depreciate the capital even when idle, unlike looms and knitting machines in the textiles industry.[31] Finally, when equipment requires higher design costs, it becomes less useful to other firms because it likely is customized to a specific production process, so it is either less productive in other uses or costs more to redeploy. For example, Ramey and Shapiro (2001) finds that equipment used in aerospace plants sells for a higher price when purchased by other aerospace firms.

While my measure of irreversibility needs to be physical, irreversibility in the *model* does not need to be. It can also arise from other sources of irreversibility, such as external financing costs and operating leverage, as long as they reduce to features of a firm's production technology. For example, demand-curve characteristics would not be admissible sources

[30] For example, see Short (2004) for an example of heavy chemical reactors. Secondary-market listings typically report the weight of looms at a few metric tons.

[31] See Jenkins (2018), Buecker and Dixon (2016).

of irreversibility because then the primitives are the preferences of a firm's customers, not the production technology.

Do I Identify the Causal Effects of Irreversibility? While the primary regression (8) provides causal estimates of the price response to credit supply shocks for high- and low-irreversibility industries, the interaction coefficient $\beta_{1,k}$ between the credit supply shock and irreversibility *cannot* be cleanly interpreted as the *causal effect of irreversibility* on the price response to credit supply shocks. Because I do not have an exogenous shifter of irreversibility in my analysis,[32] any industry characteristic correlated with irreversibility could be part of the reason why prices adjust differently. Caron (2025) shows that the estimates of $\beta_{1,k}$ have a causal interpretation only if I make the strong assumption that, conditional on covariates, the treatment effect of credit supply shocks on price changes is independent of unobserved characteristics which are correlated with investment irreversibility.[33] In the empirical analysis of Section 4.4, I perform robustness checks to show that it is reasonable to interpret my estimates of $\beta_{1,k}$ as evidence that physical sources of irreversibility change the response of prices to credit supply shocks, although the exact estimates may not be the true causal effects.

4 Evidence from Credit Supply Shocks

The regression results in this section provide evidence in support of Section 2's stylized model. Specifically, in response to the same credit supply shock, firms in industries with low investment irreversibility cut prices relative to their unaffected counterparts while firms in industries with high irreversibility do not cut their prices. This behavior is consistent with

[32] Chen et al. (2023) estimates the causal effect of a change in partial irreversibility on investment using a VAT reform in China.

[33] Caron (2025) proposes a method to estimate the causal difference for binary treatments, so I would need to extend the method to a continuous setting, which is likely a difficult task and outside the scope of the paper.

the stylized model's mechanism in which irreversibility leads to greater upward pressure on the response of prices and markups to shifts in the marginal value of liquidity.

This section first shows estimates from the main regression (8), in which I regress the year-over-year inflation rate on credit supply shocks and the interaction with investment irreversibility. I supplement these results with a similar regression run on export prices instead of the PPI sample. Then I provide supporting evidence that a difference in the customer-market incentive explains the difference in price responses to credit supply shocks. Finally, I explain why it is reasonable to interpret the difference in price responses as the result of differences in investment irreversibility and not some other characteristic correlated with irreversibility.

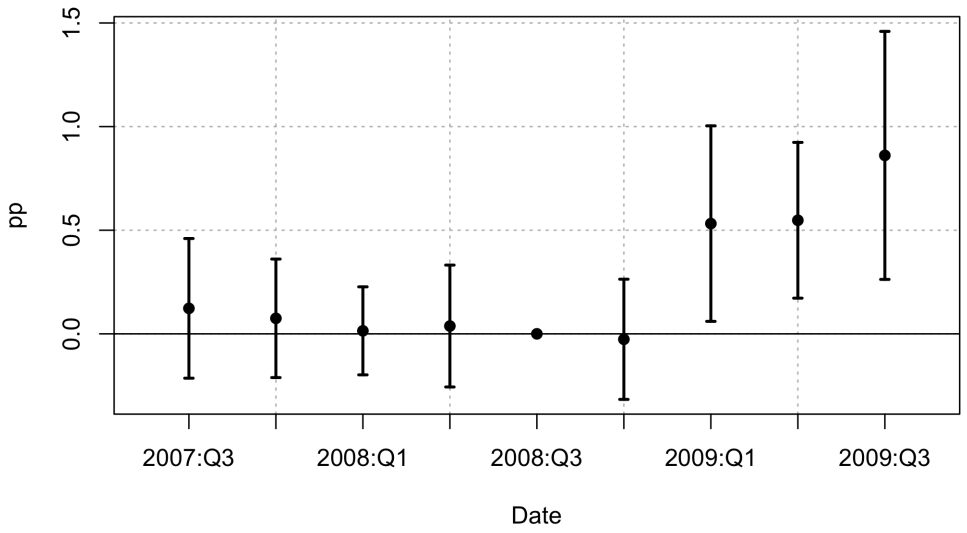
4.1 Irreversibility and the Price Responses to Credit Supply

In response to the same one standard deviation cut in credit supply, firms in industries with 1pp higher irreversibility choose a 0.86pp higher year-over-year price change in 2009:Q3. This estimate is $\beta_{1,2009:Q3}$ in the main difference-in-differences regression (8) when the interaction is linear ($H(x) = x$). Figure 2 shows the corresponding event study. The vertical axis is scaled so that each coefficient represents the effect of a 1 percentage point increase in irreversibility on the causal impact of a one standard deviation credit supply shock on a firm's price change relative to the price change the firm would have chosen in 2008:Q3. Note that this effect of irreversibility is *not* causal unless strong assumptions are invoked. There is no obvious pretrend in the four periods before 2008:Q3, but starting in 2009:Q1, firms with higher irreversibility choose higher year-over-year price changes in response to the same credit supply shock.[34]

This relative difference in pricing behavior still appears when I interact the credit supply

[34] A zero effect in 2008:Q4 is not surprising given that $\pi_{g,f,t}$ in 2008:Q4 would be the year-over-year price change in October 2008, which is only a few weeks after the Lehman bankruptcy. Firms may need more time to adjust prices.

Figure 2: More Upward Pressure on the Price Response When Irreversibility Is Higher

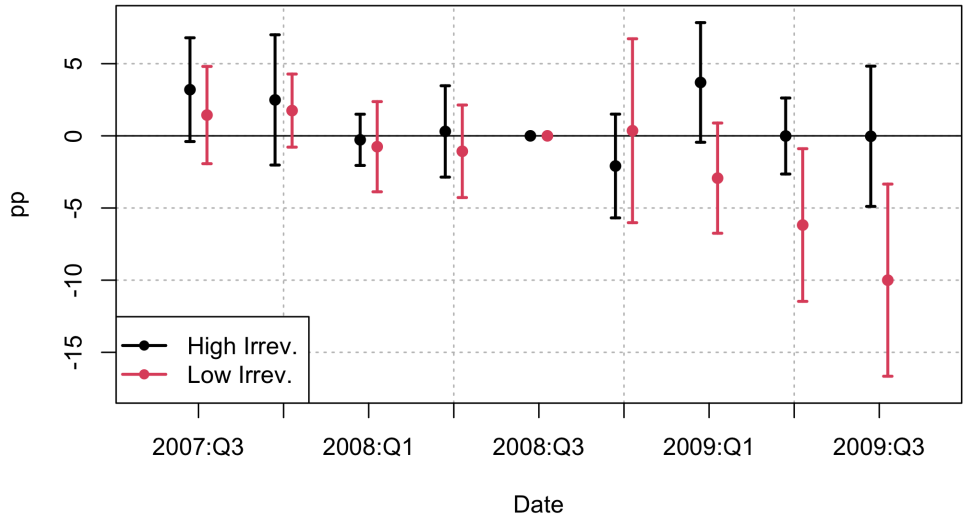


Notes: This figure shows the estimated percentage-point difference in the year-over-year log price change after a one standard deviation cut in credit supply when irreversibility increases by 1pp. The coefficients on the credit supply shock's (linear) interaction with irreversibility are instrumented with the Lehman co-syndication IV linearly interacted with irreversibility. Standard errors are clustered by primary lender, and bars are 95% confidence intervals. Any views expressed are those of the author(s) and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3211. (CBDRB-FY25-P3211-R12601). This is a part of clearance request #12601.

shock with whether a firm has above- or below-median irreversibility (i.e. $H(x) = \mathbb{1}(x \geq \text{median})$) instead of a linear interaction. Figure 3 plots the impact of the credit supply shock on the price changes for each group instead of just the relative difference. While firms in industries with low irreversibility cut prices after exposure to a credit supply shock, firms in industries with high irreversibility do not cut prices. The differences between the coefficients are also statistically significant at the 5% level over 2009:Q1–2009:Q3. The zero price change can still signify ex ante higher customer-base investment because if firms have inventories, then a firm can simultaneously cut production and inventory accumulation. The first effect decreases output sold while the second increases output sold, and it is entirely possible for

the two effects to cancel out.

Figure 3: Low-Irreversibility Firms Cut Prices While High-Irreversibility Firms Do Not



Notes: This figure shows the estimated year-over-year percentage-point log price change relative to 2008:Q3 for firms with high versus low irreversibility after a one standard deviation cut in credit supply. This behavior is surprising because the standard "ex post" intuition is that irreversibility amplifies other margins of adjustment after a cut in credit supply since firms want to limit capital sales. We would expect the red coefficients to be from high-irreversibility industries, not the black ones. However, this behavior is consistent with the "ex ante" story that tighter financial constraints make firms care more about liquidity today and less about insurance against future losses, so these firms cut back their customer investment more sharply. The coefficients on the credit supply shock and its interaction with $H(\text{Irrev})$ are instrumented with the Lehman co-syndication IV and its interaction with $H(\text{Irrev})$. Bars are 95% confidence intervals. I cluster standard errors by primary lender. Any views expressed are those of the author(s) and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3211. (CBDRB-FY25-P3211-R12601). This is a part of clearance request #12601.

The difference in year-over-year price changes across industries is quantitatively large but also not implausible. After a one standard deviation cut in credit supply, a firm in an industry with above-median irreversibility chooses a year-over-year price change that is 10pp higher than a firm in an industry with below-median irreversibility. For comparison, in Table

B.1, the standard deviation of year-over-year price changes in 2009:Q3 is 25pp.

I check the robustness of these results in the appendices. Appendix B.4 checks first-stage diagnostics. Appendix C.1 and Supplementary Appendix S3.1 check alternative choices of controls, such as the liquid share of assets, and other measures of year-over-year inflation rates. I check that other characteristics correlated with irreversibility do not explain the differences in price responses using export price data that I discuss further below.[35]

While the levels of the price responses in Figure 3 can be rationalized by the theory in Section 2, they are a surprising result because they are not consistent with the simpler intuition that greater irreversibility restricts the options available to a firm when it needs liquidity. Given previous research on price responses to credit supply shocks (e.g. Kim 2021, Renkin and Züllig 2024, Lenzu et al. accepted), a reasonable prior for the results is that firms in industries with higher irreversibility either cut prices by more or raise prices by more. Irreversibility disincentivizes capital sales, so these firms should rely more on other margins to deal with liquidity demand shocks. In other words, irreversibility constrains firms' *ex post* responses to shocks. Further, high-irreversibility firms should lean *harder* on the same margin used by low-irreversibility firms if greater irreversibility constrains a firm's ex-post response options. Thus, if the inventory incentive dominates, as in Kim (2021)'s sample, then all firms should cut prices, and firms with greater irreversibility should cut prices by more. If the customer-market incentive dominates, as in Renkin and Züllig (2024)'s sample, then all firms should hike prices, and firms in high-irreversibility industries should hike prices by more. The fact that firms with low irreversibility cut prices and that firms with high irreversibility do not in the PPI sample is difficult to explain from the ex post perspective. An ex ante story in which irreversible firms precautionarily accumulate inventory to deal with future demand shocks also does not work because then high-irreversibility firms should

[35]My access to the PPI microdata was suspended before I could check for omitted variables by including additional interactions of the credit supply shock with other characteristics.

have cut prices by more, not less.

Robustness to Export Prices. A reasonable concern is that these results may be specific to this sample of firms found in the PPI or to my choice to run the regression in growth rates instead of levels. To address these concerns, I re-run the regression analysis using export prices from the Longitudinal Firm Trade Transactions Database (LFTTD), where the left-hand-side variable is now the log price level instead of the log year-over-year price change.[36] I also use the LFTTD export price data to check two other concerns. First, the difference in price responses could result from a difference in demand elasticities across industries with high versus low irreversibility.[37] Second, the previous regressions did not saturate the covariates, so differences in pre-crisis characteristics across industries with high versus low irreversibility may explain the difference in price responses. I address these concerns with the following regression. Let $I_f = H(\text{Irrev}_{\text{ind}(f)})$, $E_g = H(\text{Elast}_g)$, and $Z_{g,f} = (I_f, E_g, I_f \times E_g)^\top$. Then I estimate

$$\begin{aligned}\log p_{g,f,t} = &\sum_{k \in T} \mathbb{1}(t=k) \left[\beta_{0,k}\left(-\Delta \widetilde{L}_f\right) + \boldsymbol{\beta}_{1,k}^\top \left(-\Delta \widetilde{L}_f \times Z_{g,f}\right)\right] \\ &+ \sum_{k \in T} \mathbb{1}(t=k) \left[\gamma_{0,k} I_f + \gamma_{1,k}^\top X_f + \gamma_{2,k}^\top (I_f \times X_f) + \gamma_{3,k}(I_f \times E_g)\right] \\ &+ \Gamma_{g,t} + \Gamma_{\text{ind}(f),t} + \varepsilon_{g,f,t}\end{aligned} \tag{9}$$

where H indicates an above-median value, $\boldsymbol{\beta}_{1,k}$ is the coefficient vector corresponding to $Z_{g,f}$, and the granularity of the product group g is HS6. The main effect of E_g in each period is absorbed by $\Gamma_{g,t}$. By additionally interacting the credit supply shock $-\Delta \widetilde{L}_f$ with the demand elasticity Elast_g, I can compare price responses across industries with different

[36] I cannot run the regression in levels on the PPI sample because my access to PPI microdata was indefinitely suspended as of September 2025 due to limited resources at the BLS to support external research projects.

[37] Kim (2021) and Renkin and Züllig (2024) both find that demand elasticity helps explain heterogeneity in how prices respond to credit supply shocks.

levels of irreversibility within each demand-elasticity group. I measure demand elasticities using estimates from Soderbery (2015), which improves upon estimates from Broda and Weinstein (2006).[38] I find that there are no significant differences in the mean demand elasticity for industries with high versus low irreversibility.[39] I interact the covariates X_f with the irreversibility indicator to better control for pre-treatment differences, although I do not also interact with the elasticity indicator to avoid too many thin cells.[40]

There is greater upward pressure on prices for exporters in industries with high irreversibility than for exporters in industries with low irreversibility after a cut in credit supply, holding constant the product-level demand elasticity group. Further, exporters of goods with low demand elasticities in high-irreversibility industries actually raise prices after a cut in credit supply, not just keep them constant. The relative difference in coefficients in 2009 is also about 10%, like the corresponding regression in Figure 3 using PPI data.[41] For goods with high demand elasticities, prices fall after a cut in credit supply, and they fall by less in industries with high irreversibility. Figure C.4 reports these results. As in the PPI sample, this difference is consistent with different ex ante customer-market incentives and inconsistent with greater ex post sensitivity by firms to credit supply shocks in high-irreversibility industries. When I do not include the demand elasticity as a third interaction with the credit supply shock, the results mirror Figure 3. I find price cuts after cuts in credit supply in low-irreversibility industries and no statistically significant price response in high-irreversibility

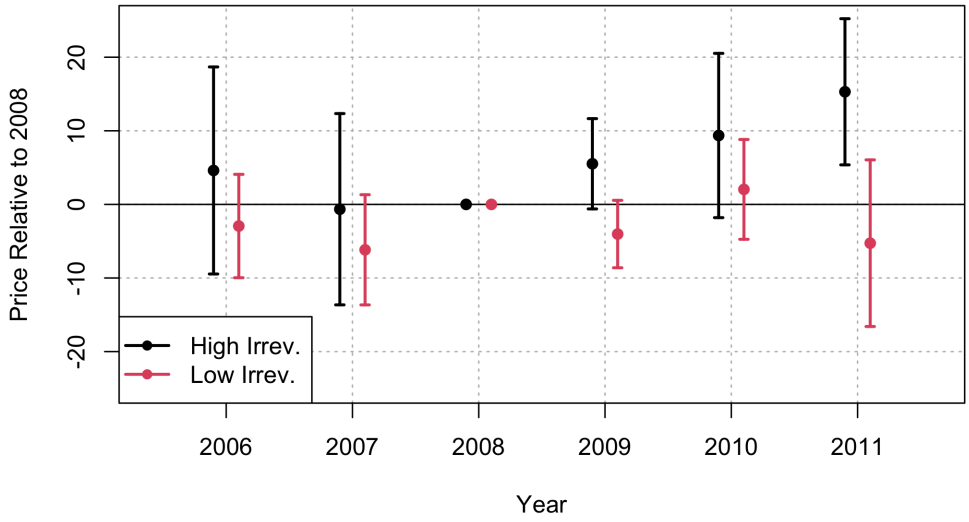
[38] An important difference is that Soderbery (2015) finds upward bias in Broda and Weinstein (2006)'s estimates. Removing this upward bias substantially lowers the median demand elasticity in less irreversible industries, notably the food and beverages industry.

[39] In the export price sample, the mean demand elasticity is also not different between high- and low-irreversibility industries with high demand elasticities or between high- and low-irreversibility industries with low demand elasticities.

[40] Because unit value prices can be noisy, I follow Renkin and Züllig (2024) and apply a two-step estimator that weights firm-product pairs inversely to the variance of their residuals from an unweighted first-step regression.

[41] I construct prices as annual unit values, and since LFTTD records data at a monthly frequency like the PPI, I use the twelve months ending in July to line up with the PPI sample. So 2009 in Figure 4 is constructed from transactions over August 2008-July 2009.

Figure 4: Exporters with High Irreversibility Raise Prices for Low Demand Elasticity Goods



Notes: This figure shows the estimated impact of a one standard deviation cut in credit supply on the log unit value price (relative to 2008) for firms with above-median irreversibility versus below-median irreversibility selling products with below-median demand elasticity. Both coefficients in 2009 are significant at the 10% level. The upward pressure on the price response in high-irreversibility industries still appears when the credit supply shock also varies with the demand elasticity. This result assuages the concern that irreversibility is a proxy for more product-market characteristics that lead to inelastic demand, such as specialized products. This figure is *not* evidence that firms in high-irreversibility industries are more ex post sensitive to credit supply shocks because I find smaller price cuts in industries with high irreversibility for high demand elasticity goods. Also, when I do not split goods into high and low demand elasticities, I get the same result that firms in high-irreversibility industries do not cut prices while firms in low-irreversibility industries cut prices after a cut in credit supply. The coefficients on the credit supply shock and its interaction with $H(\text{Irrev})$ are instrumented with the Lehman co-syndication IV and its interaction with $H(\text{Irrev})$. This is Panel (b) of Figure C.4 in Appendix C.1, which also reports the analogous above-median-demand-elasticity panel. The product-level demand elasticities are import demand elasticities from Soderbery (2015). Standard errors are clustered by primary lender, and bars are 95% confidence intervals. Any views expressed are those of the author(s) and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3432. (CBDRB-FY26-P3432-R13333). This is a part of clearance request #13333.

industries. Table C.2 reports these results.

4.2 Evidence for Differences in Customer-Market Incentives

While a difference in price responses after credit supply shocks is consistent with a difference in customer-market incentives, the reason why the prices behave differently should be a difference in the behavior of markups according to the theory in Section 2, not a difference in marginal costs. This section tests this idea by measuring markups according to the production approach in De Loecker et al. (2020) and Foster et al. (2022) using ASM/CMF data. This data is at the establishment level, so I compute a sales-weighted average markup across establishments with the same 4-digit NAICS code owned by the same firm. I do not fully aggregate to the firm level because markups may behave differently across product categories.[42] I run the LFTTD price regression (9) but use the log markup on the left-hand side and interpret 4-digit NAICS codes as product group codes.[43]

After an idiosyncratic cut in credit supply, firms in industries with high irreversibility set a higher log markup relative to firms in industries with low irreversibility and temporarily increase the log markup in absolute terms. Table 1 reports the estimates over 2008–2010. There is a marginally significant increase in the log markup in 2009 for firms with high irreversibility and a marginally significant decrease for firms with low irreversibility, and in 2010 neither estimate is significant, consistent with a temporary rise in markups. The difference in markup responses is also statistically significant at the 5% level only in 2009. The temporary nature of the absolute increase and relative difference in markups is consistent with a rise in markups by firms in high-irreversibility industries to boost short-run liquidity.

[42] When De Loecker et al. (2020) computes markups using Census data, the authors define the firm-level markup as the sales-weighted average markup across establishments with the same 4-digit NAICS code owned by the same firm.

[43] I run the regression using data over 2005–2011 to match the dates of the LFTTD sample. Recall that the LFTTD sample's data is timed so that, for example, the price in 2006 is constructed from data over August 2005 to July 2006. Because the ASM/CMF data is annual, I choose 2007 to be the reference year since production in the fourth quarter of 2008 is treated.

Table 1: Log Markups Rise in High-Irreversibility Industries

	2008	2009	2010
High Irreversibility	5.78	20.9*	8.52
	(4.39)	(11.7)	(6.62)
Low Irreversibility	1.50	−7.20*	−5.75
	(3.44)	(4.01)	(6.67)
Sig. Diff. ($p < 0.05$)	N	Y	N

Notes: This table reports the estimated coefficients on the credit supply shock (standard errors in parentheses) by above-/below-median irreversibility. A positive coefficient means that a cut in credit supply increases the log sales-weighted average markup across establishments with the same 4-digit NAICS code owned by the same firm. This table shows that a cut in credit supply causes a firm in high-irreversibility industries to raise its log markup in 2009 above the value in 2007 at the 10% level, while a firm in a low-irreversibility industry lowers its log markup at the 10% level, and the difference in responses is significant at the 5% level. I compute the establishment markup following De Loecker et al. (2020) and Foster et al. (2022). The coefficients on the credit supply shock and its interaction with H(Irrev) are instrumented with the Lehman co-syndication IV and its interaction with H(Irrev). Standard errors are clustered by primary lender. The bottom row of this table reports the significance at the 5% level of the interaction coefficient. The regression is estimated using data over 2005-2011, but I only disclose the numerical estimates in 2008-2010. The coefficients are insignificant at the 10% level in all years beside 2009. Any views expressed are those of the author(s) and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3432. (CBDRB-FY27-0044). This is a part of clearance request #13503. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.3 Supporting Descriptive Evidence

If irreversibility strengthens the customer-market incentive, then irreversibility should be strongly associated with other measures of investment in a sticky customer base. This prediction holds for two complementary notions of customer investment: contract duration and selling expenses. While this evidence is descriptive, it is favorable for this paper's argument for two reasons. First, the export price evidence shows a difference in price responses even when I control for demand elasticities, so I can address concerns about confounding demand-side characteristics that show up through product-level demand elasticities. Second,

Section 3.4 shows that my measure of irreversibility is not closely related to demand-side characteristics that would shift the returns to a customer base.

Contract Duration. Longer contract durations mitigate demand uncertainty by pinning down demand further into the future. Based on firm-to-firm contracts from goods-selling manufacturers collected by Chen et al. (2026), a 10pp increase in irreversibility is associated with a one-year increase in contract duration. While longer contracts have often been interpreted as an optimal response to relationship-specific investments,[44] the fact that my measure of irreversibility is not associated with buyer concentration in Compustat Segment suggests that differences in durations at the industry level may not be the result of relationship specificity.

Selling Expenses. Selling expenses have long been interpreted as another way to invest in a customer base. Gourio and Rudanko (2014) develops a model of customer capital due to product market frictions and supports the model with Compustat data on selling, general, and administrative expenses. Peters and Taylor (2017) and Chiavari (2026) refine this Compustat measure by stripping out unrelated components, such as R&D and rental expenses, while He et al. (2026) uses Capital IQ to directly measure selling expenses and uses SEC filing data to explain why firms use selling expenses.

These papers have typically interpreted selling expenses as a proxy for the strength of product market frictions, but this paper points out that high selling expenses could also be the result of differences in production technology. Consistent with this idea, I find that irreversibility is robustly and strongly associated with higher selling expenses in Appendix A.2, Figure A.3 and Table A.2. The results hold when I control for demand-side characteristics that could shape the return to selling expenses, such as the share of sales to households.

[44] Examples include energy markets (Joskow 1987, Von Hirschhausen and Neumann 2008, and Zahur 2026) and trucking (Hubbard 2001). On the other hand, Darmouni et al. (2026) finds that quantity contracts are used in the pulp and paper industry to mitigate demand uncertainty.

Differences in production technology may help explain why He et al. (2026) finds that some business-to-business industries spend a lot on selling expenses, despite the usual explanation that customer markets result from consumer brands or good-specific habits.

4.4 Alternative Explanations

This section considers alternative explanations for my results and argues why they are less plausible than this paper's argument that irreversibility strengthens the customer-market incentive. Table 2 summarizes this section's arguments.

Customer Markets or Firm-Specific Capital? Kermani and Ma (2023) also shows that irreversibility has positive associations with markup countercyclicality and the frequency of price adjustments, and the authors suggest that this association arises from a difference in the magnitude of desired price changes when firms have firm-specific capital instead of rented capital. The intuition for this mechanism comes from Altig et al. (2011). If capital is "firm-specific," meaning that the capital stock for current production cannot be adjusted, unlike rented capital, then firms will cut prices by less after a decline in aggregate output because firms cannot increase their capital stock to meet the extra demand due to a lower relative price.[45] If unmodeled menu costs deter firms from making small price changes, then we should expect small desired price changes to result in more inaction. Under this interpretation, greater irreversibility in an industry should also mean a lower share of rented capital, which then makes capital stocks harder to adjust in the short run.

However, two reasons lead me to prefer my explanation, which goes through customer markets. First, I find that irreversibility is associated with *more* rented capital, not less, in Figure A.4d, presumably because firms lease capital to hedge against the costs of irre-

[45]The model in Altig et al. (2011) does allow capacity utilization to vary contemporaneously. The key assumption is that the stock of capital itself for current production cannot be adjusted, whereas standard DSGE models assume capital for current production can be freely adjusted through rental markets.

Table 2: Addressing Alternative Explanations for Differences in Price Responses

Alternative	Intuition	Evidence Against This Concern
Firm-specific capital	When capital in production cannot be adjusted immediately because capital is firm-owned, firms desire smaller price changes.	Higher irreversibility is associated with *more* rented capital (Figure A.4d). Less frequent capital sales also point to irreversibility as a proxy for resale costs, not the inability to adjust capital in current production.
Differences in inventories	Inventory stocks could be smaller or harder to liquidate in high-irreversibility industries	Irreversibility is not significantly negatively associated with median inventories/sales (Figure 5) or inventory recovery rates (Figure A.1d).
Other correlated firm characteristics	Interest spread on the last loan, liquidity ratio, book leverage, PPE share of assets, or selling expenses drive the result.	The export-price result for low-elasticity goods survives additional shock interactions with each characteristic (Table C.3).
Insulation from credit supply shocks	Precautionary cash holdings reduce the need to adjust prices at all after a credit supply shock.	High-irreversibility exporters raise prices for low-elasticity goods (Figure 4), and this result is robust to adding an interaction of the liquidity ratio with the credit supply shock. High-irreversibility firms also cut employment growth more (Table C.4).
Survivorship bias	High-irreversibility firms are the firms that did not go bankrupt because they were more insulated.	Credit supply shocks do not seem to cause more deaths among Compustat firms, and death rates do not rise more in high-irreversibility industries (Supplementary Appendix S4).
Different demand elasticities	Product-market characteristics that result in more inelastic demand change the incentive to cut prices.	Export-price responses differ by irreversibility within demand-elasticity groups (Figure 4 and Appendix Figure C.4).
Capital stocks and marginal costs	Firms with high-irreversibility cut more capital, so their marginal costs are higher.	Establishment-level capital stocks significantly fall for low-irreversibility firms but not for high-irreversibility firms (Table C.5).

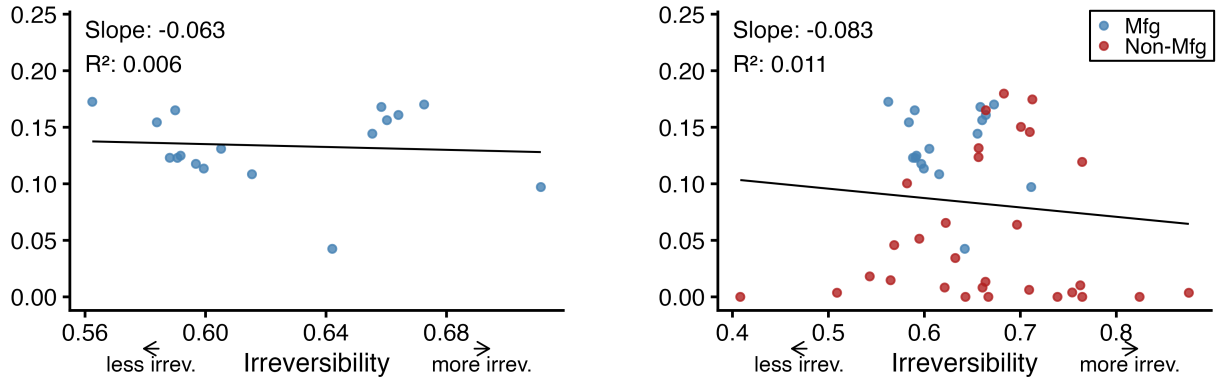
versibility (Fairhurst et al. 2026, Chowdhury et al. 2025) or low borrowing capacity (Eisfeldt and Rampini 2009, Kermani and Ma 2023). The mechanism in Altig et al. (2011) should therefore make prices less rigid in more irreversible industries since an ex ante larger share of leases makes it easier to adjust current production capacity. Second, Kermani and Ma (2023) shows that capital sales are less frequent on average in industries with higher irreversibility, consistent with larger costs to capital sales. There is no cost to capital sales in Altig et al. (2011)'s model, so there should not be a strong incentive to sell capital less frequently. In contrast, I interpret irreversibility as costly resale, and it is precisely this cost that motivates insurance through the customer base.

Why Not a Difference in Inventories? This paper argues that inventory accumulation does not explain differences in price responses due to irreversibility. In addition to the model-based discussion in Section 2, irreversibility is not significantly correlated with the median inventories/sales ratio, as Figure 5 shows. Thus, it is unlikely that firms in industries with high irreversibility do not cut prices after declines in credit supply because they have fewer inventories on hand. Irreversibility also seems unrelated to the ability of a firm to easily obtain cash from inventories according to inventory recovery rates by industry from Kermani and Ma (2023) in Appendix Figure A.1d.

Checking Correlated Characteristics. Firms increase prices by more in high-irreversibility industries for low-demand-elasticity goods even after controlling for another characteristic that could be correlated with irreversibility.[46] Specifically, I add an interaction between the credit supply shock and an additional characteristic to the export price regression (9) to check whether irreversibility is just a proxy for some other channel. The key result from Figure 4 that the price change is higher in industries with greater irreversibility for goods with low demand elasticities is robust across these characteristics: spread on the last loan,

[46] To limit the number of disclosure estimates, I only report sign and significance.

Figure 5: Median Inventories/Sales



(a) Manufacturing Only

(b) All Industries in Kermani and Ma (2023)

liquidity ratio, book leverage, PPE asset share, and SG&A to sales ratio. Riskier borrowers, more cash on hand, lower leverage, lower capital intensity as a share of assets, and more selling expenses as a share of sales do not explain why there is greater upward pressure on prices after credit supply shocks in industries with higher irreversibility. Table C.3 reports the results.

Are Firms with Greater Irreversibility Insulated from Credit Shocks? Another interpretation of Figure 3 is that firms with high irreversibility are insulated from credit supply shocks and therefore do not adjust their prices. One reason why firms with high irreversibility may be insulated is that they precautionarily hold more cash to deal with irreversibility in normal times. With more cash, these firms would not need to liquidate inventory as a way to raise liquidity and thus could keep their prices the same.

However, this explanation is inconsistent with the evidence from export prices in LFTTD and employment growth in the PPI sample. Figure 4 shows a significantly positive response for export prices of goods with low demand elasticities sold in high-irreversibility industries after cuts in credit supply. Firms that are more insulated from shocks should not hike prices. When I regress employment growth on the credit supply shock, firms in indus-

tries with high irreversibility also cut employment growth more than firms in industries with low irreversibility (see Table C.4 in Appendix C.2). While firms likely hold more cash and adjust their capital structure to help with the costs of irreversibility, this paper's evidence indicates that these adjustments in capital structure do not fully remove the incentive to invest in larger customer bases as insurance against idiosyncratic demand risk.

Firms with greater irreversibility may also have been "insulated" because of survivorship bias. My regressions involve balanced panels. If firms in high-irreversibility industries exited more, then a balanced panel may select only for firms that did not exit because they were unaffected by cuts in credit supply. Supplementary Appendix S4 mitigates this concern by showing that credit supply shocks did not cause more firm deaths among Compustat firms and that firm death rates did not rise more in industries with high irreversibility.

5 Quantification

This section considers a back-of-the-envelope exercise to show that the estimated differences in the price response to credit supply shocks between high- and low-irreversibility industries imply quantitatively meaningful effects on aggregate price rigidity. Specifically, I use my regression estimates to first predict the amount of deflation caused by credit supply shocks during the Global Financial Crisis and then compute how much more flexible prices would have been if prices in all industries responded like prices in the least irreversible industry. These estimates also point to differences in production technology as another reason, besides demand elasticities, for why Kim (2021) estimates price cuts while Renkin and Züllig (2024) estimates price increases after credit contractions.

This exercise abstracts from general equilibrium effects. To check whether indirect effects substantially change the predictions of the back-of-the-envelope exercise, I build a two-industry DSGE in which I model the difference in customer-market incentives across

industries in reduced form rather than explicitly microfounding it with a difference in partial irreversibility.

5.1 A Back-of-the-Envelope Calculation

This subsection describes the two counterfactuals behind the back-of-the-envelope calculation and reports the implied increase in aggregate price rigidity.

Procedure. I consider two counterfactuals, C1 and C2. In C1, I suppose that firms with tighter credit supply shocks than the 10th percentile have their credit counterfactually relaxed to the 10th percentile. For example, a firm whose credit supply tightened by a 90th percentile amount now counterfactually borrows from a bank that only experienced a 10th percentile credit supply shock. I then use the empirical estimates from the primary regression (8), in which I regress the year-over-year log price change using PPI data on the credit supply shock, its linear interaction with irreversibility (i.e. the specification for Figure 2), and controls to predict the price change for all goods produced by firms in a given industry. In particular, I use log price changes over July 2008–2009 from publicly available goods-level price indices from the BLS PPI, concord these indices to 2-digit SIC codes, compute the average counterfactual credit supply shock for each 2-digit SIC code, and use the coefficient estimates from the regression (8) to compute the counterfactual price change implied by the average credit supply shock.[47] Note that I apply the same adjustment to the price of every good mapped to the same 2-digit SIC industry, and this adjustment takes into account the level of irreversibility in a firm's industry. I do not apply a price adjustment to goods indices which do not link to an SIC code in Kermani and Ma (2023)'s dataset. I use credit supply

[47] I use public goods-level price indices because I computed this back-of-the-envelope calculation after my access to the microdata was indefinitely suspended. I use price changes over July 2008–2009 to align with the timing used by the regressions on the PPI microdata. Specifically, I define the year-over-year price change for a quarter based on the year-over-year change in the first month of the quarter. Thus, the year-over-year price change underlying the 2009:Q3 coefficient is the change over July 2008–2009.

shocks from firms in Dealscan for which I can compute credit supply shocks, not just firms in the PPI or LFTTD samples.[48] Finally, I aggregate the goods-level counterfactual price changes using the PPI's importance weights on each goods index.[49]

In counterfactual C2, I perform the same procedure but I adjust price responses using the estimates for the least irreversible industry among the 2-digit SIC codes that are linked to the goods-level price indices. Note that this counterfactual C2 does not capture the *causal* effect of a change in irreversibility. Instead, it shows how aggregate prices would behave if we could change each industry's characteristics that are correlated with irreversibility to the characteristics of the least irreversible industry. Nevertheless, it is still a useful way to gauge the magnitude of the estimated effects, even if a causal interpretation is difficult to credibly make.

Results. In both counterfactuals, credit supply shocks cause additional deflation, and the magnitudes are large. The actual PPI fell by about 19% over July 2008–2009.[50] The first counterfactual suggests that credit supply shocks cause over 7% more deflation. If we could hypothetically change the irreversibility (and correlated characteristics) of the industries in the PPI sample to the irreversibility of the least irreversible industry, then the additional deflation increases to nearly 12%. This additional deflation implies that prices would fall by 39.1% less because of differences in irreversibility (and correlated characteristics) across industries.

[48] This sample is the same as the one I use in Supplementary Appendix S3.2 to study the extensive margin effects of the credit supply shock, so I also require these borrowers to have non-missing loan and borrower characteristics in Dealscan.

[49] I have checked that an aggregation of the goods-level price indices using weights from the BLS nearly replicates the official PPIACO series in FRED.

[50] This PPI is the aggregation of the goods-level indices using 2008 importance weights.

Table 3: Back-of-the-Envelope Counterfactuals

	Actual	C1	C2
Percent Price Change	-19.0	-11.8	-7.1
Deflation Due to Credit Supply Shocks		-7.3	-11.9
% More Rigidity in C1 vs. C2			39.1

Notes: This table shows that aggregate prices fall by less and are thus "more rigid" after credit supply shocks compared to the counterfactual scenario in which prices in all industries responded like prices in the least irreversible industry. Percent changes in this table are log point changes. The Actual column reports the percent change in the aggregate PPI index computed by aggregating goods-level price indices using the 2008 importance weights over July 2008–2009. The other two columns report the predicted percent change in the aggregate PPI index in the two counterfactuals and use the Actual column (Column 1) to back out the effect of credit supply shocks on aggregate prices. C1 relaxes firm-specific credit supply shocks larger (and tighter) than the 10th percentile to the 10th percentile, holding each industry's actual level of irreversibility fixed. Counterfactual C2 applies the same credit easing as C1, but additionally assumes prices in all industries respond like prices in the least irreversible industry in the sample. The final row computes how much less prices fell in C1 versus C2 and normalizes by the predicted deflation due to credit supply shocks in C2. Any views expressed are those of the author(s) and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3211. (CBDRB-FY25-P3211-R12601). This is a part of clearance request #12601.

5.2 What About General Equilibrium?

Since the back-of-the-envelope exercise abstracts from general equilibrium effects, I cannot rule out that the predicted additional rigidity due to irreversibility would vanish if I accounted for general equilibrium forces. To assuage this concern, Appendix F and Supplementary Appendix S8 build a medium-scale two-industry DSGE that account for general equilibrium effects on inflation through the nominal wage, aggregate demand, and the real interest rate. I mirror counterfactuals C1 and C2 by comparing the inflation response to credit supply shocks when there is a stronger customer-market incentive in one industry (C1) and when both industries have weak customer-market incentives (C2).

Since the point of this model is just to check whether general equilibrium effects nullify

the back-of-the-envelope estimate, I choose a reduced-form modeling device that generates a difference in customer-market incentives across industries to simplify the DSGE and its calibration. The modeling device adds a non-pecuniary preference to the firm objective for making sales to the same customer over time, mirroring how goods-specific habits create a preference for purchases from the same firm. This paper's core mechanism is that irreversibility affects real price rigidity because it strengthens the customer-market incentive, so what actually matters for aggregate price rigidity is the difference in the customer-market incentive across industries. The DSGE would be much more complicated if I microfounded the difference in customer-market incentives by extending the model in Section 2 into an infinite-horizon setting with heterogeneous firms. I leave this extension for ongoing work in Chen (2026). Further, since idiosyncratic uncertainty is far larger for most firms than aggregate uncertainty (see Bloom et al. 2018), aggregate shocks probably do not have substantial effects on the interaction between irreversibility and the customer-market incentive. Thus, a microfoundation is probably not quantitatively crucial for the first-order effects of MIT shocks to aggregate credit supply.

I find that general equilibrium forces attenuate the back-of-the-envelope's predicted increase in price rigidity by 49.2%. The primary reason is the behavior of real interest rates. Firms rely more on cutting their inventory stocks to deal with the cut in credit supply in counterfactual C2 compared to C1. Inflation falls by more as a result. Since monetary policy follows a Taylor rule which cuts the nominal rate when inflation deviates from target, real interest rates endogenously fall by more, too. Because lower real interest rates incentivize firms to hold onto their inventory stocks, the endogenously larger cut in real interest rates causes firms to cut inventories less intensively, which dampens the fall in inflation and brings the total inflation response in C2 closer to ther esponse in C1. If we neglect the real interest rate's indirect effect on inflation, then the remaining indirect effects attenuate the back-of-the-envelope's prediction about the increase in price rigidity by only 21.5%.

6 Conclusion

This paper shows that investment irreversibility leads to greater real price rigidity because irreversibility strengthens the customer-market incentive. The reason is that irreversibility makes a sticky customer base valuable as insurance against bad idiosyncratic demand shocks in the future. Using producer and export price microdata as well as markups from manufacturing microdata, I find empirical evidence in support of this ex ante mechanism.

These results can help central banks when they make forecasts during financially driven recessions. A key concern during any recession is the behavior of inflation because central banks use inflation as a gauge to determine the appropriate size of their interest rate response. Forecasting inflation during financially driven recessions may be especially difficult given the literature's conflicting evidence on whether financial shocks tend to push prices up or down. While inventory stocks are observable, the customer-market incentive is not easily measured. Financially driven recessions may also be concentrated in specific industries. This paper's results offer the following guidance. Suppose a large financial shock occurs. A central bank can combine proxies for physical irreversibility in its own economy with predictions of which industries will be hit harder by the shock. If the shock tends to affect very irreversible industries, then the central bank can predict that inflation will likely fall by less because the shock will affect industries with stronger customer-market incentives.

I leave several avenues for future research. In ongoing work in Chen (2026), I am developing a heterogeneous-firm model with partially irreversible investment, customer markets, and endogenous demand uncertainty. That paper aims to show that differences in irreversibility can generate quantitatively significant differences in the customer-market incentive in general equilibrium. Investment irreversibility can also be seen as one specific example of the broader problem of operating leverage in the presence of uninsurable demand risk. Bad demand shocks are especially painful when a firm has costs it must pay because

it cannot scale down its operations. Other input adjustment frictions generate operating leverage and could therefore shape a firm's incentive to acquire a sticky customer base. For example, human capital is a significant and partially irreversible investment by firms because workers acquire human capital over time and are imperfectly substitutable. Jäger et al. (2024) estimates that workers are very costly to replace due to imperfect substitutability, and Meeuwis et al. (2025) shows that firms respond to risk-premium shocks by firing workers whose human capital is easier to replace. When firms find it harder to replace their workers, they may invest more in sticky customer bases to ensure that they do not need to frequently adjust their employment.

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Appendices

A Descriptive Evidence about Irreversibility

A.1 Irreversibility and Demand-Side Characteristics

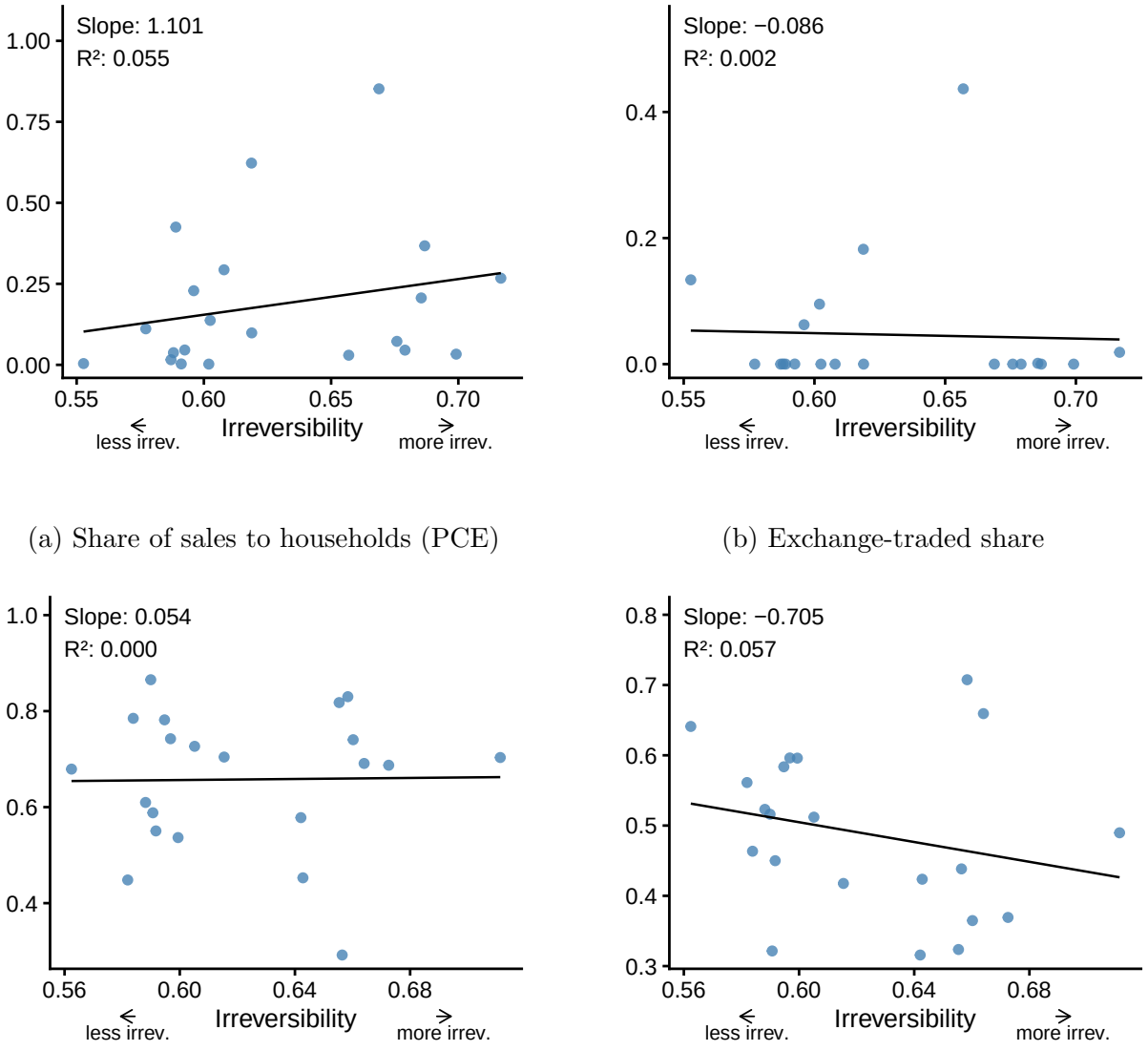
This appendix provides descriptive evidence that my measure of physical irreversibility does not appear to be a proxy for specific demand-side characteristics that might influence the incentive to accumulate a customer base or otherwise shape price responses to credit supply shocks. Figures A.1 and A.2 plot these relationships for manufacturing and mining industries. I specifically consider these characteristics, in order: (i) share of private domestic sales to households (PCE), (ii) share of output classified as exchange-traded according to the conservative classification of Rauch (1999), using domestic-shipment weights, (iii) share of Compustat firms reporting a major customer in Compustat Segment, (iv) inventory liquidation recovery rate from Kermani and Ma (2023), (v) share of output classified as a durable good, and (vi) purchase frequency by households from the Consumer Expenditure survey.

A.2 Irreversibility and Customer Markets

This appendix provides descriptive evidence that irreversibility and customer markets interact. In particular, industries with more irreversible investment also exhibit behaviors consistent with greater investment in future demand. While this evidence does not directly show that firms adjust prices differently in industries with higher irreversibility, as the theory predicts in Section 2, this descriptive evidence provides further support for the idea that irreversibility interacts with investment in a sticky customer base.

Contract Durations. Manufacturing firms in more irreversible industries sign longer contracts on average. This behavior is consistent with the idea that irreversibility amplifies the

Figure A.1: Investment Irreversibility and Demand-Side Characteristics



(a) Share of sales to households (PCE)

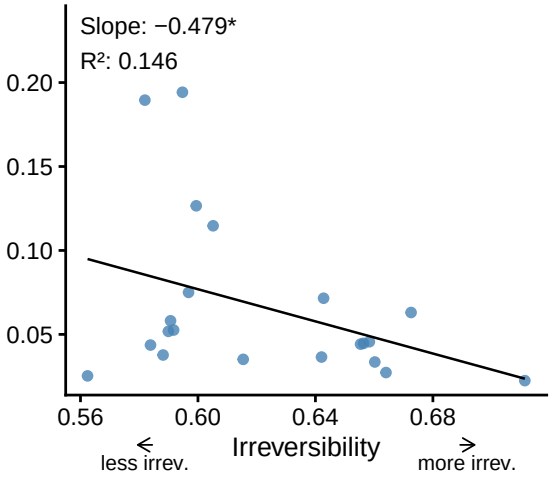
(b) Exchange-traded share

(c) Share of firms reporting a major customer

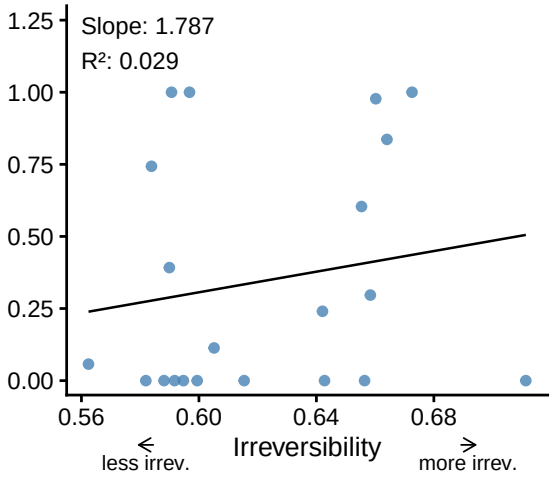
(d) Inventory liquidation recovery rate

Notes: Manufacturing and mining industries. Share of sales to households is the 1997 PCE share of private domestic sales. The exchange-traded share uses the conservative classification of Rauch (1999) and product weights from the 1997 Economic Census (Census of Manufactures and Census of Mineral Industries). Major-customer reporting share uses Compustat Segment data over 1997–2019. Inventory liquidation recovery rates are from Kermani and Ma (2023). The OLS estimates use robust standard errors. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

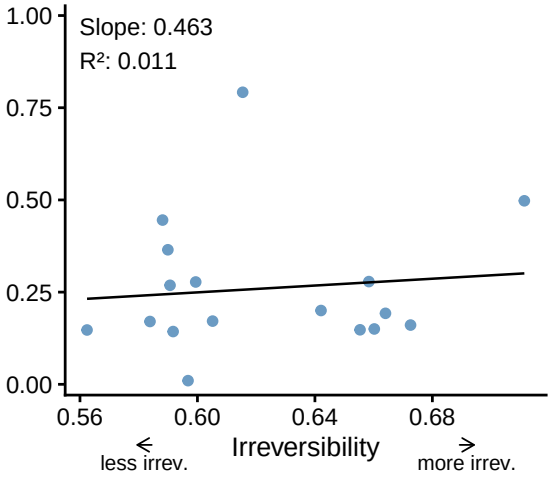
Figure A.2: Investment Irreversibility and Demand-Side Characteristics



(a) Producer concentration (HHI of sales)



(b) Share of output that is durable



(c) Household purchase frequency

Notes: Manufacturing and mining industries. Purchase frequency uses Consumer Expenditure survey diary data for 2004–2007. Mining industries lack purchase-frequency data. The OLS estimates use robust standard errors. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

cost of bad demand shocks, so firms in a more irreversible industry want to lock in demand for a longer period of time because longer contract durations give firms more certainty about their future sales. Table A.1 shows this result by regressing the duration of a contract's initial term on my measure of irreversibility. Some contracts have fixed term lengths, but others have an initial term length and then automatically renew unless one side wants to terminate or renegotiate. Column (2) restricts attention to contracts with no auto-renewal clause. The sample is limited to manufacturing firms since coverage is more complete in the contracts data from Chen et al. (2026).[51] The positive coefficients in Table A.1 indicate that firms in more irreversible industries lock up their demand further into the future by signing longer contracts. The magnitude is also quantitatively meaningful. A difference of 10 percentage points in the degree of irreversibility is associated with an increase in the average contract duration by about a year.

Table A.1: Contract Duration and Investment Irreversibility

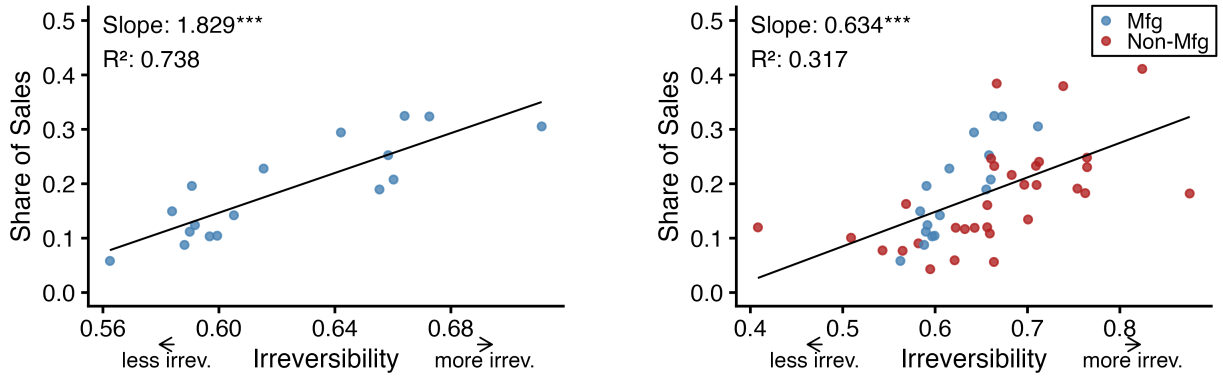
	Duration	
	(1)	(2)
Irreversibility (pp)	1.20**	1.30**
	(0.51)	(0.49)
Include Auto-Renewals	Y	N
R^2	0.234	0.251
Industries	17	17
Contracts	908	589

Notes: Relationship between contract duration and irreversibility of tangible capital at the 2-digit SIC industry level for manufacturers. Contracts in the sample are goods contracts from U.S. manufacturing sellers filed over 2001-2026. Column (2) restricts to the subset of contracts without auto-renewal clauses. The outcome variable is the average duration in months. The units of irreversibility is measured in percent so that the coefficient represents the association with an increase in irreversibility by 1pp. Robust standard errors are reported. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[51] A contract is included in the sample if the *seller*'s industry is manufacturing, the seller is domiciled in the U.S., the seller provides a good to the buyer, and the contract is not a distribution contract.

Selling Expenses. Industries with higher irreversibility also devote a larger share of sales to selling expenses, which are another way that firms can accumulate a larger customer base. Following Chiavari (2026), I compute selling expenses from Compustat as Selling Expenses = xsga − xrent − xpr − recd − xrd − rdip. This measure takes SG&A expenses and subtracts out costs unrelated to customer acquisition.[52] Figure A.3 plots median selling expenses divided by sales over 1997-2019 against irreversibility by 2-digit SIC industry, separately for manufacturing and again for all industries. The relationship is strong. Among manufacturers, the R^2 is very high at 0.73. Across all industries, the R^2 weakens, but the relationship is still positive and significant. The weaker relationship suggests that the relationship between demand uncertainty and investment irreversibility of tangible capital matters less outside of manufacturing. The mean version involves larger coefficients because of outliers that increase the mean selling expense to sales ratio.

Figure A.3: Selling Expenses / Sales Positively Correlate with Investment Irreversibility



(a) Manufacturing Only

(b) All Industries in Kermani and Ma (2023)

This relationship is robust across aggregation choices and definitions of the selling expenses ratio. The same results apply when I use the mean instead of the median or

[52] xrent = rental expenses (e.g. structures, operating leases), xpr = pension and retirement expenses, recd = doubtful or uncollectible receivables, xrd = R&D expenses, and rdip = in-progress R&D expenses. I follow Peters and Taylor (2017) and do not remove xrd and rdip when xrd > xsga and xrd < cogs since R&D expenses are sometimes put under COGS.

the ratio of industry-total selling expenses to industry-total sales instead of a firm-weighted statistic. I also check robustness to Peters and Taylor (2017)'s measure of selling expenses, which only strips out R&D costs, and SG&A expenses, as in Gourio and Rudanko (2014). Results are available upon request.

The relationship between investment irreversibility and selling expenses is robust and stable to the inclusion of demand-side controls. predicts Table A.2 reports the relationship between irreversibility and the He et al. (2026) and Chiavari (2026) measures of selling expenses, with and without controls for an industry's share of sales to households, inventory recovery rates from Kermani and Ma (2023) and the share of firms reporting a major customer. The point estimates do not change much when I add controls. I choose these specific measures because they are available across most industries. The Rauch (1999) commodity classification, for example, only applies to goods.

Table A.2: Selling Expenses and Investment Irreversibility with Demand-Side Controls

	HMS median S&M / revenue		Chiavari median selling / sales	
	(1)	(2)	(3)	(4)
Irreversibility	0.1464**	0.1420*	0.4905***	0.4860***
	(0.0674)	(0.0741)	(0.1079)	(0.1285)
Demand-Side Controls	N	Y	N	Y
N	42	42	43	43
R^2	0.146	0.189	0.369	0.501

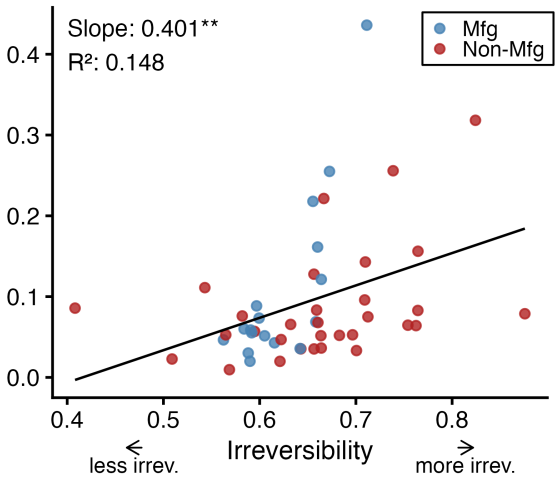
Notes: This table regresses two different measures of selling expenses on the irreversibility measure and checks that their point estimates are stable when I control for four demand-side characteristics: share of sales to households, inventory recovery rates from Kermani and Ma (2023), share of firms reporting a major customer, and HHI concentration. I choose this subset of characteristics because the others are not available for a broad range of industries. Each reported coefficient is scaled so that it is the percentage point response to a one percentage point increase in irreversibility. Robust standard errors are reported. * $p < .10$, ** $p < .05$, *** $p < .01$.

A.3 Correlations of Irreversibility with Other Characteristics

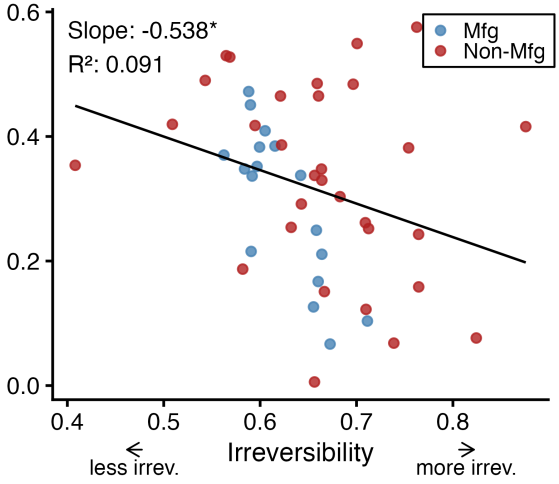
At the 5% significance level, higher irreversibility is associated with higher cash/assets, a higher operating lease share, a higher perceived discount rate, and a lower frequency of price adjustment, and, at the 10% level, with lower book leverage.[53] The association with discount rates is consistent with the idea that irreversibility increases the hurdle rate for investments.

[53]The industry characteristics are measured using Compustat data over the years 1997-2019, with the exception of the operating lease capital share, for which I use data over 2019-2025, and capital intensity, which is measured using BLS industry data. For any firm-year-level characteristic, I aggregate by taking the median within an industry. The frequency of price adjustment is computed by Pasten et al. (2020) using PPI data over 2005-2011 concorded to the BEA summary level, and the perceived discount rates are from Gormsen and Huber (2022).

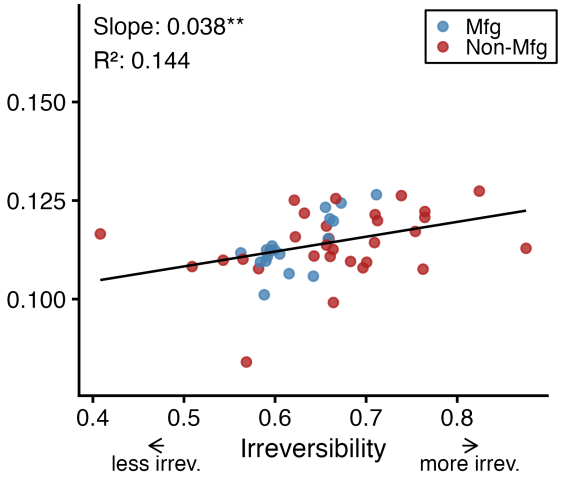
Figure A.4: Characteristics of Irreversible Industries



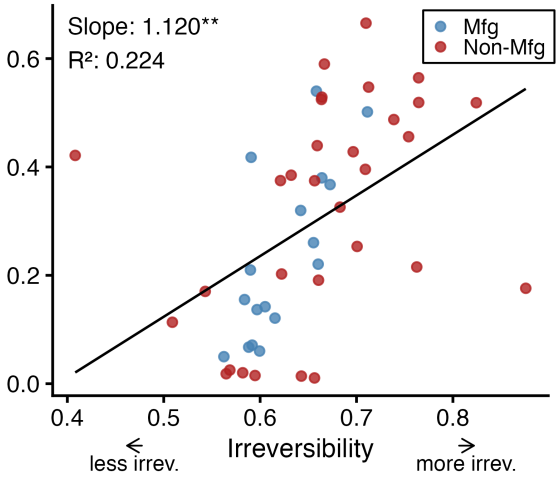
(a) Cash / Assets



(b) Book Leverage

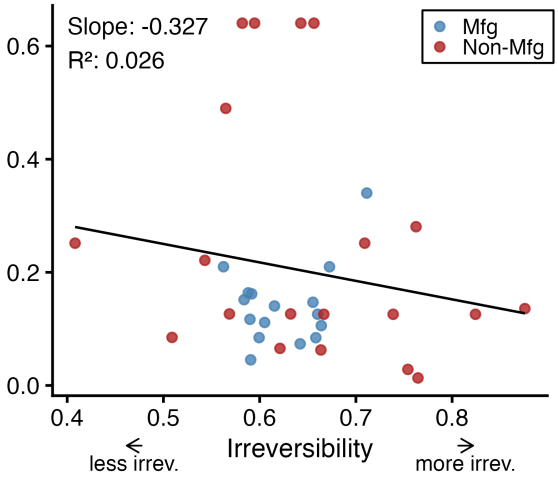


(c) Perceived Discount Rate

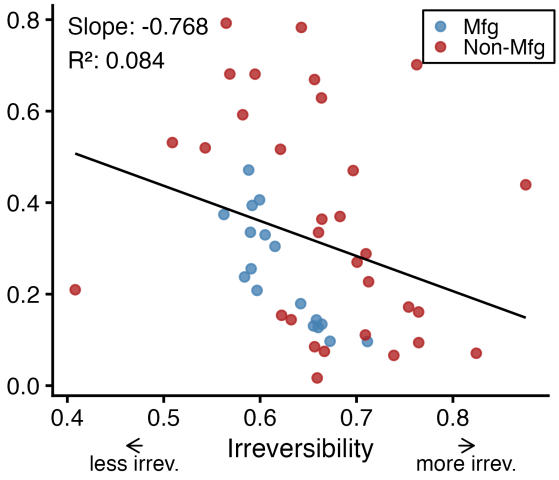


(d) Operating Lease Capital Share

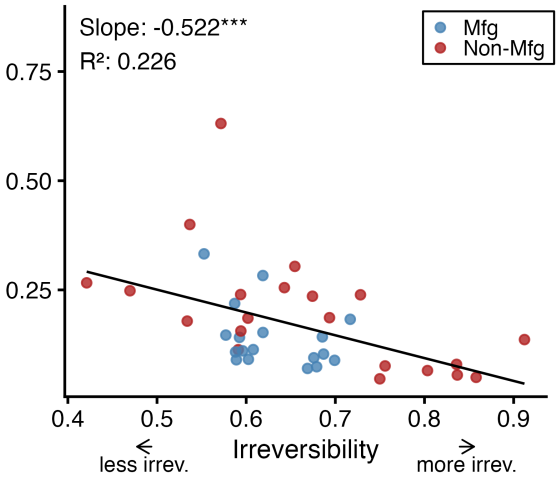
Figure A.5: Characteristics of Irreversible Industries



(a) Capital Intensity



(b) PPENT / Assets



(c) Freq. of Price Adjustment

B Diagnostic Checks for Empirical Analysis

B.1 Summary Statistics

Table B.1: Summary Statistics of the PPI-Census-Dealscan Dataset

Variable	N	Mean	SD	P10	P50	P90
Public	350	0.86				
Manufacturer	350	0.57				
Bond Access	350	0.57				
Credit Supply Shock (Dealscan)	350	0.42	0.12	0.28	0.41	0.56
Lehman Co-Syndication IV (%)	350	0.89	0.42	0.56	0.79	1.3
Employment (Mar. 2007)	350	17900	42800	724	5520	35700
Last Loan Amount (mil.)	350	711	1270	45	300	1600
Age	350	38.5	11.2	32	32	58
Irreversibility (%)	350	63	5	57	62	71
Last Loan All-In Spread (bp)	350	114	91.5	25.5	75.5	250
Last Loan Maturity (months)	350	53.6	14.5	36	60	62
Loan Due	350	0.23				
YoY % Price Chg. 2009:Q3	350	-6.65	25.1	-38	0	8.2

Notes: Manufacturers form a majority of the sample, but the PPI also surveys firms in many other industries, including mining, agriculture, retail, and wholesale trade. A firm's industry code comes from Census Bureau data, but the PPI may collect prices on products unrelated to a firm's primary industry. Any views expressed are those of the author(s) and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3211. (CBDRB-FY25-P3211-R12601). This is a part of clearance request #12601.

B.2 Khwaja and Mian (2008) Test

This appendix reports the Khwaja and Mian (2008) test discussed in Section 3.3. In short, this test considers firms which signed a new loan over 2008:Q4-2009:Q2 and computes the growth in lending for each lender-firm pair across lenders in the firm's last syndicate. Note that many lenders will extend zero dollars to the firm in the post-Lehman period, so my

measure of the lending change must allow for zeros. I consider two versions. First, the lending change is $\log(1+\text{loan}_{\text{post}}) - \log(\text{loan}_{\text{last}})$. Second, I use the Davis et al. (1996) (DHS) growth rate.

With this data, I regress the change in lending on the firm-bank credit supply shock $\Delta L_{f,b}$ and either observable firm characteristics or a borrower fixed effect. Under certain assumptions, the bias introduced when firm-bank matching is not as good as random equals the difference in the point estimates for the coefficient on $\Delta L_{f,b}$ across these two specifications. Because my sample size falls substantially, I adjust the covariates from the baseline sample to make the regression estimable. Specifically, I use 2-digit NAICS fixed effects instead of 3-digit, an indicator for whether a loan was due instead of the bins for the number of loans due, an indicator for bond issuance or not, group together firms whose last loan was signed in 2004 or earlier, and drop altogether the indicator for whether a firm had multiple leads in the pre-period. As Table B.2 shows, the point estimates are quite close to each other. The differences have similar magnitudes to what Chodorow-Reich (2014) and Kim (2021) find.

Table B.2: Khwaja and Mian (2008) Test

	(1)	(2)	(3)	(4)
-$\Delta L_{f,b}$	-2.49^{***}	-2.43^{***}	-0.33^{***}	-0.30^{***}
	(0.40)	(0.43)	(0.05)	(0.05)
Borrower FE	Y	N	Y	N
Controls	N	Y	N	Y
R-Squared	0.31	0.22	0.40	0.26
Observations	350	350	350	350

Note: Estimates of the coefficient on the firm-bank credit supply shock $-\Delta L_{f,b}$. The outcome variable in columns (1)-(2) is the log growth and in columns (3)-(4) is the DHS growth rate. The columns differ in the covariates used (borrower FE or observables). Standard errors are two-way clustered by firm and bank. Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3211. (CBDRB-FY25-P3211-R12601). This is a part of clearance request #12601. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B.3 Balance of the Lehman Instrument

Table B.3 reports the association between the Lehman co-syndication instrument and observed firm characteristics. The Lehman co-syndication IV is generally not associated with observable covariates. The only variables that are statistically significant at the 5% level are the interest rate spread, bond access, and book leverage. I control for the first two covariates in all regressions, and when I add book leverage as well as other balance sheet controls in Appendix C.1, the results still hold.

Table B.3: Balance Test of Observables with Lehman Co-Syndication IV

Variable	Association	Variable	Association
Last Loan All-In Spread (bp)	$+^{****}$	PPENT/Assets	+
Age	+	Liq. Assets/Assets	−
Last Loan Maturity (months)	+	Book Leverage	$+^{**}$
Bond Access	$+^{***}$	Interest/Debt	+
Public	+	Inventory/Sales	−
Loan Due	+	Inventory/Assets	−
Loan Issued After 2005	+	PPENT	+
Multiple Leads on Last Loan	+	Assets	+
Multiple Leads on A Loan in 2006Q4-7Q2	+	Sales	+
Employment (Mar. 2007)	+	Log(Inventory)	+
Irreversibility (pp)	+	Log(Assets)	+
Last Loan Amount (mil.)	+	Log(Liq. Assets)	+
Recoverable PPENT/Assets	+		

Sign and significance when I regress firm characteristics on the Lehman co-syndication IV to check whether these characteristics are balanced. Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3211. (CBDRB-FY25-P3211-R12601). This is a part of clearance request #12601. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B.4 First-Stage Diagnostics

Table B.4 reports first-stage diagnostics for the instrumental-variables specification. Note that the credit supply shock is the same in every period for the main diff-in-diff, so I run the first stage for a single period. When using the Lehman co-syndication IV as a single instrument for the credit supply shock (no interaction with irreversibility), Olea and Pflueger (2013)'s robust test for a weak IV rejects the null hypothesis when using the standard critical value of 10%. In the case of a single endogenous regressor that is just identified, Angrist and Kolesár (2024) recommends that researchers screen by the sign of the first stage predicted by economic theory. I find that the first stage for (8) is positive and statistically significant at the 5% level. This sign is precisely what I expect a priori: higher exposure due to co-syndication with Lehman predicts a higher value of $-\Delta\widetilde{L}_f$, i.e. tighter credit supply.

Table B.4: Olea and Pflueger (2013) Weak IV Test

Statistic	Estimate
Eff. F-Stat	69.4
Crit. Val. for 10%	23.1

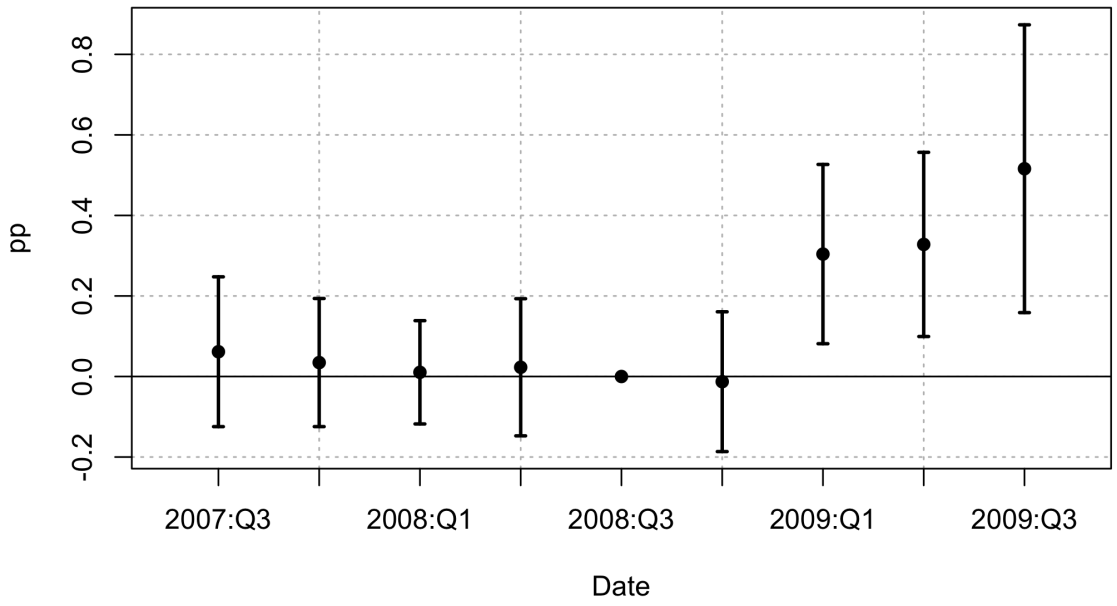
Note: The effective F-stat from Olea and Pflueger (2013)'s robust test for weak IVs is large and exceeds the critical value for a maximum relative bias of 10%. Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3211. (CBDRB-FY25-P3211-R12601). This is a part of clearance request #12601.

C Additional Results Using Credit Supply Shocks

C.1 Robustness Checks for Price Regressions

Results Using Lehman Co-Syndication IV. Figure C.1 shows the reduced-form estimate of $\beta_{1,k}$ when using the Lehman co-syndication IV. Figure C.2 shows the estimate of $\beta_{1,k}$ when book leverage, average interest rate, cash-to-assets ratio, and inventory-to-sales ratio are added as additional covariates.

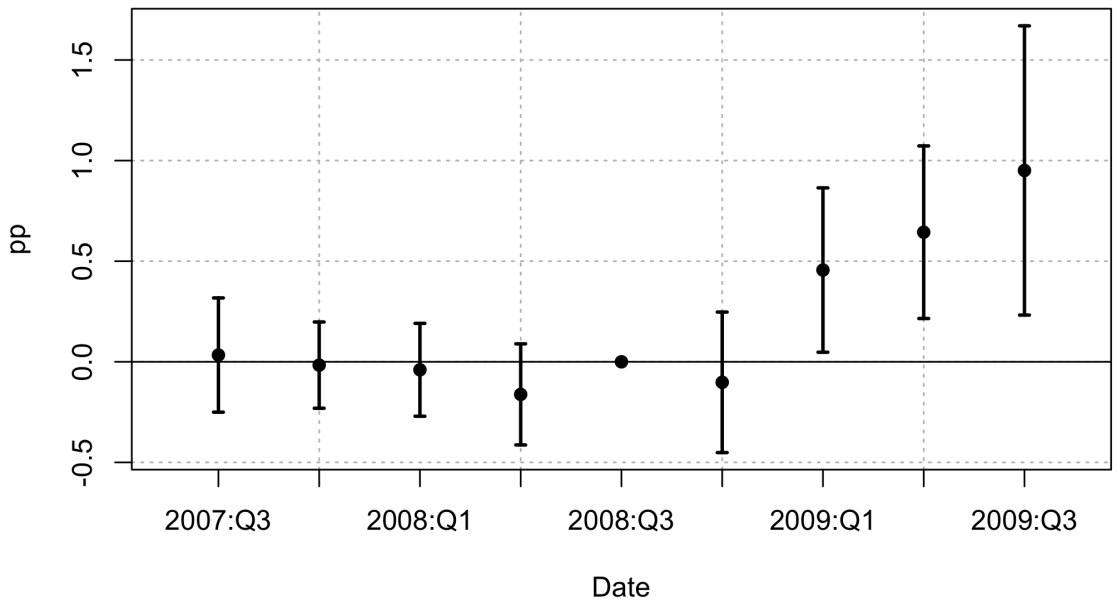
Figure C.1: Reduced Form of Regression with Linear Interaction in Main Text



Note: The figure displays the estimated coefficients and confidence intervals for the primary specification. Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3211. (CBDRB-FY25-P3211-R12601). This is a part of clearance request #12601.

In addition to these diff-in-diffs, I verify that the sign and significance of $\beta_{1,2009:Q3}$ remains robust across a variety of other specifications. The sign and significance at the 5%

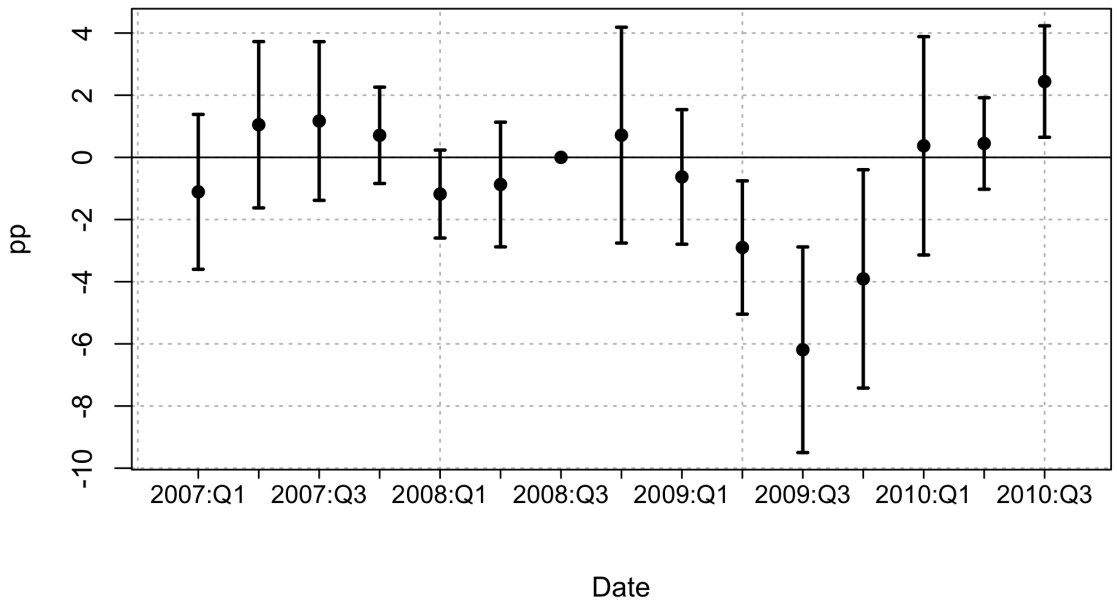
Figure C.2: Adding Balance Sheet Controls to Baseline Regression in Main Text



Note: This figure presents estimated effects when I also include as covariates the liquid assets ratio, book leverage, average interest rate on debt, and inventory to sales ratio measured in 2007. Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3211. (CBDRB-FY25-P3211-R12601). This is a part of clearance request #12601.

level is unchanged when I use 2-digit NAICS instead of 3-digit (with and without balance sheet controls) or proxy irreversibility with one minus the actual time-averaged recovery rate *without projecting onto physical attributes*. If I construct the outcome variable by first aggregating to a single price within a year-quarter as an average or geometric average of all items within a 4-digit NAICS by buyer type product group and then computing year-over-year log price changes from the aggregated index, the sign on the coefficient in 2009:Q3 remains the same, but it is no longer significant. However, the sign and significance of the interaction coefficient in 2009:Q1 remains positive at the 5% level. This result could stem from measurement error since a product group at the 4-digit NAICS level does combine many

Figure C.3: Effects on Prices Over a Longer Horizon



Note: This figure regresses the year-over-year price change on the instrumented credit supply shock over 2007:Q1-2010:Q3. Due to sample size concerns, this regression does not check for heterogeneous effects across high/low irreversibility industries. Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3211. (CBDRB-FY25-P3211-R12601). This is a part of clearance request #12601.

different types of products. My baseline measure avoids this measurement error because I compute goods-level inflation rate, which compares the price over time for the exact same good, and then average across goods to the product group level to get an inflation rate.

Export Prices. My results are robust to export prices, as discussed in the main text. A key advantage of the export price data is that I can check the role of demand elasticities. Kim (2021) and Renkin and Züllig (2024) find that the demand elasticity in a product market explains heterogeneity in how prices responds to credit supply shock. Figure C.4 reports the event-study figures for both high and low demand elasticity groups. The difference in

point estimates are larger for low demand elasticities while the difference for goods with high demand elasticities are marginally significant at the 10% level. However, alternative specifications in which vary how I construct the unit-value price lead to significance at the 5% level. Table C.1 reports those results. Notably, while the baseline results show only marginally significant differences in the relative price response for goods with high demand elasticities, alternative constructions of the unit-value price show stronger significance. I also use the export price data to check for omitted variables that could be correlated with irreversibility and are alternative explanations for my results in Table C.3 .

Table C.1: Sign and Significance of Price Responses Using Alternative Unit-Value Price Measures

Price measure	2009	2010	2011
A. Price response within HL			
Geometric Weighted Average, No Constrained Elasticity Estimates	$+^{*}$	$+^{*}$	$+^{***}$
Geometric Weighted Average	$+$	$+^{*}$	$+^{**}$
Weighted Average, No Constrained Elasticity Estimates	$+$	$+$	$+^{***}$
Weighted Average	$+$	$+^{*}$	$+^{**}$
B. Price response within LL			
Geometric Weighted Average, No Constrained Elasticity Estimates	$-^{*}$	$+$	$-$
Geometric Weighted Average	$-$	$-$	$-$
Weighted Average, No Constrained Elasticity Estimates	$-^{**}$	$+$	$-$
Weighted Average	$-$	$-$	$-$
C. Price response within HH			
Geometric Weighted Average, No Constrained Elasticity Estimates	$-$	$-$	$-^{***}$
Geometric Weighted Average	$+$	$+$	$-$
Weighted Average, No Constrained Elasticity Estimates	$-$	$+$	$-$
Weighted Average	$+$	$+$	$-$
D. Price response within LH			
Geometric Weighted Average, No Constrained Elasticity Estimates	$-^{***}$	$-^{***}$	$-^{***}$
Geometric Weighted Average	$-^{***}$	$-^{***}$	$-^{***}$
Weighted Average, No Constrained Elasticity Estimates	$-^{***}$	$-^{***}$	$-^{***}$
Weighted Average	$-^{***}$	$-^{***}$	$-^{***}$
E. Relative price response: HL − LL			
Geometric Weighted Average, No Constrained Elasticity Estimates	$+^{**}$	$+$	$+^{***}$
Geometric Weighted Average	$+$	$+^{**}$	$+^{**}$
Weighted Average, No Constrained Elasticity Estimates	$+^{***}$	$+$	$+^{***}$
Weighted Average	$+^{*}$	$+^{*}$	$+^{**}$
F. Relative price response: HH − LH			
Geometric Weighted Average, No Constrained Elasticity Estimates	$+$	$+^{*}$	$+^{*}$
Geometric Weighted Average	$+^{**}$	$+^{**}$	$+^{**}$
Weighted Average, No Constrained Elasticity Estimates	$+^{**}$	$+^{***}$	$+^{***}$
Weighted Average	$+^{***}$	$+^{***}$	$+^{***}$

Note: The first letter of each group denotes high (H) or low (L) irreversibility; the second denotes high or low demand elasticity. Panels A–D report the sign and significance of each group's credit-supply-shock coefficient; panels E and F report differences between high- and low-irreversibility groups within each demand-elasticity group. Rows compare geometric and arithmetic weighted averages of unit values, with and without constrained elasticity estimates. The baseline results in the main text correspond to "Geometric Weighted Average, No Constrained Elasticity Estimates." Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3432. (CBDRB-FY26-P3432-R13333). This is a part of clearance request #13333. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.2: Sign and Significance of Export Price Responses by Irreversibility Only

Price measure	2009	2010	2011
A. High irreversibility			
Geometric Weighted Average, No Constrained Elasticity Estimates	$+$	$+$	$+$
Geometric Weighted Average	$+$	$+^{*}$	$+$
B. Low irreversibility			
Geometric Weighted Average, No Constrained Elasticity Estimates	$-^{***}$	$-^{*}$	$-^{**}$
Geometric Weighted Average	$-^{**}$	$-^{*}$	$-^{**}$
C. Relative price response: High − Low			
Geometric Weighted Average, No Constrained Elasticity Estimates	$+^{***}$	$+^{**}$	$+^{***}$
Geometric Weighted Average	$+^{**}$	$+^{***}$	$+^{**}$

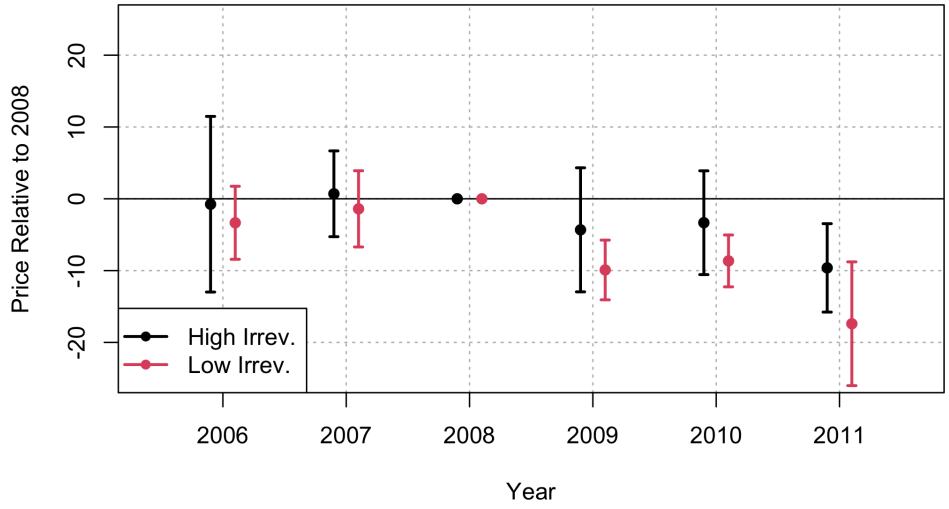
Note: This table shows that the responses of export prices to credit supply shocks in high- versus low-irreversibility industries resemble the responses in the PPI data. Thus, the split by demand elasticity simply uncovers the fact that, for sufficiently inelastic demand, the customer-market incentive becomes strong enough that firms in high-irreversibility industries hike their prices instead of merely neglecting to cut them. Panels A and B report the sign and significance of the credit-supply-shock coefficient for firms in high- and low-irreversibility industries, where the credit supply shock is not interacted with the demand elasticity. Panel C reports the difference between the high- and low-irreversibility coefficients. Rows are alternative constructions of the log unit-value price; the first row, "Geometric Weighted Average, No Constrained Elasticity Estimates," is the baseline. Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3432. (CBDRB-FY26-P3432-R13333). This is a part of clearance request #13333. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table C.3: Checks for Omitted Variable Bias in Treatment Effects

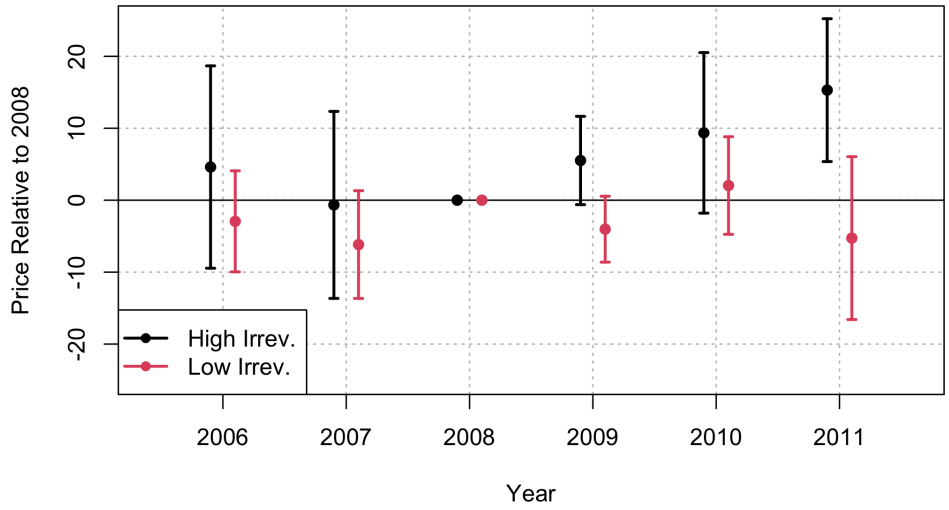
Additional control	2009	2010	2011
A. Relative price response: HL − LL			
Baseline	$+^{**}$	$+$	$+^{***}$
Spread on last loan	$+^{**}$	$+$	$+^{***}$
Liquid assets / assets	$+^{***}$	$+$	$+$
Book leverage	$+^{***}$	$+$	$+^{**}$
PPE / assets	$+^{***}$	$+$	$+^{***}$
SG&A / sales	$+^{**}$	$-$	$+$
B. Relative price response: HH − LH			
Baseline	$+$	$+^{*}$	$+^{*}$
Spread on last loan	$+$	$+$	$+^{*}$
Liquid assets / assets	$+$	$+$	$+$
Book leverage	$+$	$+$	$-$
PPE / assets	$+$	$+$	$+$
SG&A / sales	$+^{*}$	$+$	$+$
C. Price response within HL			
Baseline	$+^{*}$	$+^{*}$	$+^{***}$
Spread on last loan	$+$	$+^{*}$	$+^{***}$
Liquid assets / assets	$+^{*}$	$+$	$-$
Book leverage	$+$	$+$	$+$
PPE / assets	$+^{**}$	$+^{**}$	$+^{**}$
SG&A / sales	$+^{**}$	$+$	$-$

Note: HL, LL, HH, and LH refer to the irreversibility by demand elasticity bin, so HL refers to high-irreversibility and low demand elasticity. Panels A and B report the significance of the difference in price responses to the credit supply shock across industries with high versus low irreversibility for products with similar demand elasticities. Baseline reports the regression from the main text. The remaining rows check robustness to adding additional characteristics as interactions with the credit supply shock. All characteristics are predetermined variables measured before the Lehman bankruptcy. Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3432. (CBDRB-FY27-P3432-R13463). This is a part of clearance request #13463. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Figure C.4: Prices Also Respond Differently to Credit Supply Shocks for Exporters



Panel (a): High Demand Elasticity



Panel (b): Low Demand Elasticity

Notes: Each panel plots the estimated impact of a credit supply shock on the log unit value price (relative to 2008) for firms with above-median irreversibility (black) versus below-median irreversibility (red) selling products with above-median demand elasticity (panel (a)) versus below-median demand elasicity (panel (b)). The product-level demand elasticities are import demand elasticities from Soderbery (2015). Standard errors are clustered by primary lender, and bars are 95% confidence intervals. Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3432. (CBDRB-FY26-P3432-R13333). This is a part of clearance request #13333.

C.2 Employment Growth

I compute the firm-level annual growth rate in employment in March using LBD data.[54] Table C.4 reports the sign on the interaction between the credit supply shock and irreversibility as well as the predicted impact on employment growth for firms with irreversibility at the 90th percentile. The growth in employment from Mar. 2008 to Mar. 2009 is not statistically different across industries with high or low irreversibility, but the growth in employment from Mar. 2009 to Mar. 2010 is lower for firms in industries with higher irreversibility. For a 1pp increase in irreversibility, the impact on employment growth is about -0.6pp lower. The second row in the table confirms that firms with irreversibility at the 90th percentile cut employment growth by almost 9pp over Mar. 2009-2010 after a cut in credit supply.[55]

[54] I also remove the product group by time fixed effect and log of employment from the controls to avoid any spurious correlation. Then I add the firm's lagged employment growth (as a time-varying control) to account for the persistence of employment growth and the weighted employment growth across counties in which a borrower has establishments to control for local demand shocks that might be driving a borrower's employment response. The regression uses employment data over 2006-2010. Coefficients are relative to 2008, which is the impact of the credit supply shock on employment growth from Mar. 2007 to Mar. 2008. Note that the time-varying lagged employment growth may be a bad control, but that fact, if anything, should attenuate the estimated effects.

[55] No standard error is reported for Mar. 2008-2009 because, to limit the number of disclosed estimates, I did not disclose the covariance term needed to correctly compute the standard error of the predicted impact.

Table C.4: Firms with High Irrev. Cut Employment More After Credit Supply Shock

Year	2009	2010
	(1)	(2)
CSS $\times$Irrev$_{\text{ind}(f)}$	0.060	-0.613^{**}
	(0.289)	(0.291)
Predicted Effect, P90 Irreversibility	1.731	-8.623^{**}
		(3.254)

Notes: This table report the coefficient on a linear interaction between the credit supply shock and the irreversibility as well as the predicted effect of the credit supply shock on employment growth when irreversibility is at the 90th percentile. Column (1) is Mar. 2008-2009 and (2) is Mar. 2009-2010. No standard error is reported for the predicted effect in Column (1) to limit the number of disclosed estimates. I cluster standard errors by primary lender. Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3211. (CBDRB-FY25-P3211-R12601). This is a part of clearance request #12601. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C.3 Establishment Capital and Inventory Responses

The following table uses establishment-level data on capital equipment and inventory stocks. I find evidence that firms in high-irreversibility industries do not cut their equipment stocks after a cut in credit supply, consistent with an unwillingness to downscale capital, while firms in low-irreversibility industries do seem to cut their equipment stock. These cuts are large enough that the log equipment and structures capital stock also falls at the 10% level in 2009 for low-irreversibilty firms. Consistent with the cut in prices by low-irreversibility firms, their log inventory stocks significantly decline over 2008-2009. Note that this data is annual and based on the calendar. year, so the data in 2008 refers to equipment and inventory stocks at the end of 2008. Thus, the statistically negative effect in 2008 for inventories does not raise an identification concern.

Table C.5: Capital Stock and Inventory Responses from the LFTTD Sample

	2008	2009	2010
Equipment			
High Irreversibility	−	−	−
Low Irreversibility	−0.029	−0.049*	−
	(0.022)	(0.025)	
Inventory			
High Irreversibility	+	+	−
Low Irreversibility	−0.11**	−0.13**	−
	(0.05)	(0.06)	

Notes: This table reports the effect of the credit supply shock on establishment-level log equipment and log inventory stocks relative to 2007 for firms in high- versus low-irreversibility industries. To limit the number of disclosed estimates, I only report the magnitudes of coefficients for firms in low-irreversibility industries over 2008-2009. For other years and for high-irreversibility firms, I report only sign and significance. Consistent with irreversibility inducing more inaction, firms with high irreversibility do not significantly cut their capital stocks while firms with low irreversibility do. The point estimates for firms with low irreversibility are also lower than for firms with high irreversibility. Consistent with a fall in prices, firms in low-irreversibility industries cut their inventory stocks whereas firms in high-irreversibility industries do not. Standard errors are clustered by a firm's primary lender. Any views expressed are those of the author(s) and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3432. (CBDRB-FY26-P3432-R13333). This is a part of clearance request #13333. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

D Proofs for the Partial-Equilibrium Model

This appendix solves the two-period model of Section 2 backward, from the afternoon of $t = 1$ to $t = 0$, and proves Propositions 2.1 and 2.2. I will occasionally define new non-primitive terms to keep the math compact. I will use time subscripts or explicit parenthetical arguments for new terms that are functions of endogenous choices. Non-primitive terms are purely functions of parameter primitives. Supplementary Appendix S5.1 states a regularity condition on parameters that ensures capital sales occur in equilibrium.

D.1 Setup

Demand. Let $\widetilde{\theta} \equiv \theta(1-\eta)$. The demand curves (1) are

$$\begin{aligned} y_0 &= p_0^{-\eta}, \\ y_1^z &= (p_1^z)^{-\eta}\, \mathcal{H}(y_0 \mid z), \\ \mathcal{H}(y_0 \mid z) &\equiv z + \chi y_0^{\widetilde{\theta}}, \end{aligned} \tag{D.1}$$

where $\mathcal{H}(y_0 \mid z)$ is the level of $t = 1$ demand in state $z \in \{B, G\}$, where $B < G$. The probability of each state is $1/2$, for simplicity. The marginal increase in demand from higher sales in $t = 0$ is given by

$$\mathcal{H}'(y_0) \equiv \chi\widetilde{\theta}\, y_0^{\widetilde{\theta}-1} \geq 0. \tag{D.2}$$

Because the increase is the same in either state, I omit the dependence on z.

Production, Investment, and Dividends. Output is $y_0 = k_0^\alpha \ell_0^{1-\alpha}$ at $t = 0$ and $y_1^z = (k_1^z)^\alpha (\ell_1^z)^{1-\alpha}$ in the afternoon of $t = 1$, where $k_1^z = (1-\delta)k_0 + i_1^z$. Investment expenses in the

morning of $t = 1$ is $\Phi_\kappa(i) \equiv \max\{i, (1-\kappa)i\}$. Dividends in each period are given by

$$d_0 = p_0 y_0 - w\ell_0, \quad d_1^z = p_1^z y_1^z - w\ell_1^z - \Phi_\kappa(i_1^z),$$

and the firm maximizes the present value of dividends in (2), subject to a multiplier φ on d_0 representing the marginal value of liquidity. The model ends after the afternoon of $t = 1$, and capital cannot be sold for an additional return.

Parameter Restrictions. These are technical regularity restrictions rather than economically meaningfully assumptions: $\eta > 1$, $\alpha, \delta \in (0,1)$, $\kappa \in (0,1)$, $\chi \geq 0$, and $\widetilde{\theta} \in [0,1)$.

D.2 The Firm's Problem at $t = 1$

I solve $t = 1$ taking y_0 as given, so the demand level $H \equiv \mathcal{H}(y_0 \mid z)$ is known in both the morning and the afternoon. Write $\bar{k} \equiv (1-\delta)k_0$ for the depreciated capital stock the firm brings into the morning.

Afternoon. Because y_1^z does not affect demand in any later period, the afternoon problem is static. Producing y with capital k costs

$$C(y,k) \equiv w\, y^{\frac{1}{1-\alpha}} k^{-\frac{\alpha}{1-\alpha}},$$

and the marginal cost is

$$mc(y,k) = \frac{w}{1-\alpha}\, y^{\frac{\alpha}{1-\alpha}} k^{-\frac{\alpha}{1-\alpha}}. \tag{D.3}$$

I define

$$\widetilde{\alpha}_k \equiv \frac{\alpha(\eta-1)}{1+\alpha(\eta-1)} \in (0,1),$$

which satisfies

$$1-\widetilde{\alpha}_k = \frac{1}{1+\alpha(\eta-1)}, \quad \widetilde{\alpha}_k = \alpha(\eta-1)(1-\widetilde{\alpha}_k).$$

Given demand $H>0$ and capital $k>0$, the firm sets $p_1 = \frac{\eta}{\eta-1}\, mc(y_1,k)$, and its profit is

$$\pi_1(H,k) \equiv \max_{y>0} \left\{ H^{1/\eta} y^{1-1/\eta} - C(y,k) \right\} = \bar{A}\, H^{1-\widetilde{\alpha}_k} k^{\widetilde{\alpha}_k}, \tag{D.4}$$

where

$$\bar{A} \equiv \frac{1+\alpha(\eta-1)}{\eta} \left[\frac{(\eta-1)(1-\alpha)}{\eta w} \right]^{(\eta-1)(1-\alpha)(1-\widetilde{\alpha}_k)} > 0.$$

It can be shown that the profit function π_1 is jointly concave in (H,k).

Morning. After observing z, the firm chooses k_1 to maximize afternoon profit minus investment expenses. By (D.4), its optimized dividend is $d_1^z = T(\mathcal{H}(y_0 \mid z);\kappa)$, where

$$T(H;\kappa) \equiv \max_{k_1>0} \left\{ \bar{A}\, H^{1-\widetilde{\alpha}_k} k_1^{\widetilde{\alpha}_k} - \Phi_\kappa(k_1 - \bar{k}) \right\}. \tag{D.5}$$

For a price of capital $p_k \in (0,1]$, let

$$\widehat{k}(p_k) \equiv \left(\frac{\widetilde{\alpha}_k \bar{A}}{p_k} \right)^{\frac{1}{1-\widetilde{\alpha}_k}}, \tag{D.6}$$

$$R_H(p_k) \equiv \max_{k>0} \left\{ \bar{A}\, k^{\widetilde{\alpha}_k} - p_k\, k \right\} = (1-\widetilde{\alpha}_k) \bar{A}\, \widehat{k}(p_k)^{\widetilde{\alpha}_k}. \tag{D.7}$$

The first is the capital per unit of demand that the firm wants when capital trades at p_k. The second is afternoon profit per unit of demand minus investment expenses.

Lemma D.1. *(a) The function R_H satisfies*

$$R'_H(p_k) = -\widehat{k}(p_k),$$
$$\frac{\partial R_H(1-\kappa)}{\partial \kappa} = \widehat{k}(1-\kappa) > 0.$$

(b) The optimal capital choice k_1^* in (D.5) is

condition	k_1^*	$T(H;\kappa)$
(sell) $\widehat{k}(1-\kappa)H < \bar{k}$	$\widehat{k}(1-\kappa)H$	$R_H(1-\kappa)H + (1-\kappa)\bar{k}$
(inaction) $\widehat{k}(1)H \le \bar{k} \le \widehat{k}(1-\kappa)H$	$\bar{k}$	$\bar{A}\,H^{1-\widetilde{\alpha}_k}\bar{k}^{\widetilde{\alpha}_k}$
(buy) $\widehat{k}(1)H > \bar{k}$	$\widehat{k}(1)H$	$R_H(1)H + \bar{k}$

(D.8)

(c) $T(\cdot;\kappa)$ is concave, with

$$T_H = (1-\widetilde{\alpha}_k)\bar{A}\left(\frac{k_1^*}{H}\right)^{\widetilde{\alpha}_k}.$$

In particular, $T_H = R_H(1-\kappa)$ in the sell region and $T_H = R_H(1)$ in the buy region.

(d) In the sell region,

$$\frac{\partial T}{\partial \kappa} = k_1^* - \bar{k} < 0, \quad \frac{\partial^2 T}{\partial \kappa\, \partial H} = \widehat{k}(1-\kappa) = \frac{k_1^*}{H} > 0.$$

In the interior of the inaction and buy regions, T and T_H do not depend on κ.

Proof. (a) The envelope theorem applied to (D.7) gives $R'_H(p_k) = -\widehat{k}(p_k)$.

(b) The firm buys capital at price 1 and sells it at price $1-\kappa$. So it buys up to $\widehat{k}(1)H$

if it holds less than that, sells down to $\widehat{k}(1-\kappa)H$ if it holds more than that, and otherwise keeps $\bar{k}$. When the firm actively adjusts capital at price p_k, substituting $k_1^* = \widehat{k}(p_k)H$ into (D.5) gives

$$T = R_H(p_k)H + p_k\bar{k}.$$

(c) It is straightforward to show that T is concave. The formula for T_H follows from the envelope theorem, and the special cases from $k_1^*/H = \widehat{k}(p_k)$.

(d) In the sell region, $T = R_H(1-\kappa)H + (1-\kappa)\bar{k}$. Differentiating with part (a) gives

$$\frac{\partial T}{\partial \kappa} = \widehat{k}(1-\kappa)H - \bar{k}, \quad \frac{\partial^2 T}{\partial \kappa\, \partial H} = \widehat{k}(1-\kappa).$$

The inaction and buy rows of (D.8) do not contain κ. □

Intuition for Proposition 2.2. Since $d_1^z = T(\mathcal{H}(y_0 \mid z); \kappa)$, the customer-market incentive in (3) is

$$\lambda = \frac{1}{R}\,\mathbb{E}\left[\frac{\partial d_1^z}{\partial y_0}\right] = \frac{1}{2R}\sum_{z\in\{B,G\}} T_H\big(\mathcal{H}(y_0 \mid z); \kappa\big)\,\mathcal{H}'(y_0), \tag{D.9}$$

which is positive when $\chi\widetilde{\theta} > 0$ because $T_H > 0$ by Lemma D.1(c). When the firm strictly sells capital in the bad state and does not sell in the good state, Lemma D.1(d) gives the derivatives in Section 2:

$$\begin{aligned}
\frac{\partial d_1^B}{\partial \kappa} &= i_1^B < 0, \\
\frac{\partial^2 d_1^B}{\partial y_0\, \partial \kappa} &= \widehat{k}(1-\kappa)\,\mathcal{H}'(y_0) = \frac{\partial i_1^B}{\partial y_0} > 0, \\
\frac{\partial d_1^G}{\partial \kappa} &= \frac{\partial^2 d_1^G}{\partial y_0\, \partial \kappa} = 0.
\end{aligned}$$

D.3 The Firm's Problem at $t = 0$

Let $\nu \equiv \alpha/(1-\alpha)$ and $\varsigma \equiv 1/\eta + \nu$. The firm's profit, marginal revenue, and marginal cost in $t = 0$ are

$$\pi_0(y) \equiv y^{1-1/\eta} - C(y, k_0), \quad mr_0(y) \equiv \left(1 - \frac{1}{\eta}\right) y^{-1/\eta}, \quad mc_0(y) \equiv mc(y, k_0).$$

The marginal loss on a sale at $t = 0$ is

$$L(y) \equiv mc_0(y) - mr_0(y),$$

the amount by which the marginal cost of the sale exceeds its marginal revenue. By (D.5), the firm chooses y_0 to maximize

$$J(y) \equiv \varphi\, \pi_0(y) + \frac{1}{2R} \sum_{z \in \{B,G\}} T\big(\mathcal{H}(y \mid z); \kappa\big).$$

The firm's FOC is

$$\varphi\, L(y_0) = \lambda(y_0), \tag{D.10}$$

where $\lambda(y)$ is (D.9) evaluated at $y_0 = y$. Since $mr_0(y_0) = \frac{\eta-1}{\eta} p_0$, dividing (D.10) by φ gives the main-text price equation (3).

Proof of Proposition 2.1. Assume $\chi\widetilde{\theta} > 0$, so that $\lambda > 0$. First, I prove that $y_0(\varphi)$ is a strictly decreasing function. Fix $\varphi' > \varphi$ and let $y = y_0(\varphi)$. By (D.10), $L(y) = \lambda(y)/\varphi > 0$, so

$$J'(y; \varphi') = J'(y; \varphi) - (\varphi' - \varphi)L(y) = -(\varphi' - \varphi)L(y) < 0.$$

Since $J(\cdot;\varphi')$ is strictly concave, $J'(\cdot;\varphi')$ is strictly decreasing. Because $J'(y;\varphi') < 0$ and because J is strictly concave, the root $y_0(\varphi')$ must increase J' up, hence $y_0(\varphi') < y = y_0(\varphi)$.

The price $p_0 = y_0^{-1/\eta}$ therefore strictly increases in φ, and so does the markup

$$\mu_0 \equiv \frac{p_0}{mc_0(y_0)} = \frac{1-\alpha}{w}\, k_0^{\nu}\, y_0^{-\varsigma}.$$

Assume that, for each z, $\mathcal{H}(y_0 \mid z)$ lies in the interior of a region of Lemma D.1(b), so that λ is differentiable at y_0. Define the elasticities

$$\epsilon_L(y) \equiv \frac{d\log L(y)}{d\log y}, \tag{D.11}$$

$$\epsilon_\lambda(y) \equiv -\frac{d\log \lambda(y)}{d\log y}, \tag{D.12}$$

Since $L'(y) = \nu\, mc_0(y)/y + mr_0(y)/(\eta y) > 0$ and $L(y_0) > 0$, $\epsilon_L(y_0) > 0$. By (D.9) and (D.2),

$$\lambda(y) = \frac{\chi\widetilde{\theta}}{2R}\, y^{\widetilde{\theta}-1} \sum_{z\in\{B,G\}} T_H\big(\mathcal{H}(y \mid z);\kappa\big).$$

Since $\mathcal{H}(y_0 \mid z)$ lies in the interior of a region, T_H is differentiable there. Taking logarithms and differentiating in $\log y$ gives

$$\epsilon_\lambda(y) = 1 - \widetilde{\theta} - \frac{y\,\mathcal{H}'(y)\sum_{z\in\{B,G\}} T_{HH}\big(\mathcal{H}(y \mid z);\kappa\big)}{\sum_{z\in\{B,G\}} T_H\big(\mathcal{H}(y \mid z);\kappa\big)}.$$

The fraction is weakly negative because T is concave, so $T_{HH} \le 0$, while $\mathcal{H}'(y) \ge 0$ and $T_H > 0$ by Lemma D.1(c). Hence $\epsilon_\lambda(y_0) \ge 1 - \widetilde{\theta} > 0$. Differentiating the logarithm of (D.10) in $\log\varphi$ gives

$$\frac{\partial \log y_0}{\partial \log \varphi} = -\frac{1}{\epsilon_L(y_0) + \epsilon_\lambda(y_0)} < 0,$$

$$\frac{\partial \log p_0}{\partial \log \varphi} = \frac{1}{\eta(\epsilon_L(y_0) + \epsilon_\lambda(y_0))} > 0,$$
$$\frac{\partial \log \mu_0}{\partial \log \varphi} = \frac{\varsigma}{\epsilon_L(y_0) + \epsilon_\lambda(y_0)} > 0.$$

□

Proof of Proposition 2.2. The proof follows these steps. First, I compute a number of expressions that will be used to perform the main proof. Second, I show that irreversibility wedge κ increases the elasticity by showing the FOC $J'(y_0) = 0$ takes a log-linear form in $\log y_0$ with slope S_0. The wedge κ only shifts the level of the FOC (changes y_0), *but* the elasticity of y_0 with respect to φ does not directly depend on κ. Instead, it depends solely on ω_0. However, shifts in κ shift y_0, which then shifts ω_0.

Useful Expressions: Suppose that at y_0 the firm strictly sells capital in the bad state and strictly buys capital in the good state. Supplementary Appendix S5.1 gives a condition on parameters, Assumption S5.1, under which this behavior is optimal. In these regimes, Lemma D.1(c) gives $T_H = R_H(1-\kappa)$ in the bad state and $T_H = R_H(1)$ in the good state. Then (D.9) becomes $\lambda(y) = A(\kappa)\, y^{\widetilde{\theta}-1}$, where

$$A(\kappa) \equiv \frac{\chi^{\widetilde{\theta}} \left[R_H(1-\kappa) + R_H(1)\right]}{2R}. \tag{D.13}$$

Substituting into (D.10) gives

$$\varphi\, L(y_0) = A(\kappa)\, y_0^{\widetilde{\theta}-1}.$$

Taking logarithms gives

$$\log \varphi + \log L(y_0) = \log A(\kappa) + (\widetilde{\theta} - 1) \log y_0.$$

Let $\omega_0 \equiv L(y_0)/mc_0(y_0)$ be the share of marginal cost at $t = 0$ that marginal revenue does not cover. Since $L(y_0) > 0$ and $mr_0(y_0) > 0$, $\omega_0 \in (0, 1)$. By (D.3), $mc_0(y)$ is proportional to y^ν, and $mr_0(y)$ is proportional to $y^{-1/\eta}$. So $L'(y) = \nu\, mc_0(y)/y + mr_0(y)/(\eta y)$, and

$$\epsilon_L(y) = \frac{y\, L'(y)}{L(y)} = \frac{\nu\, mc_0(y) + mr_0(y)/\eta}{mc_0(y) - mr_0(y)}.$$

At $y = y_0$, dividing the numerator and the denominator by $mc_0(y_0)$ and using $mr_0(y_0)/mc_0(y_0) = 1 - \omega_0$ gives

$$\epsilon_L(y_0) = \frac{\nu + (1 - \omega_0)/\eta}{\omega_0} = \frac{\nu + 1/\eta}{\omega_0} - \frac{1}{\eta} = \frac{\varsigma}{\omega_0} - \frac{1}{\eta}.$$

In the regimes of Assumption S5.1, $\epsilon_\lambda(y_0) = 1 - \widetilde{\theta}$. The elasticity of the FOC with respect to y is

$$S_0 \equiv \epsilon_L(y_0) + \epsilon_\lambda(y_0) = \frac{\varsigma}{\omega_0} - \frac{1}{\eta} + 1 - \widetilde{\theta},$$

which is positive because $\varsigma/\omega_0 - 1/\eta > \varsigma - 1/\eta = \nu > 0$.

Proof of Part (i): higher irreversibility raises sales at $t = 0$, $\partial \log y_0/\partial\kappa > 0$. Recall the first-order condition (D.10) of the objective J, which under this proposition's assumption becomes

$$\log \varphi + \log L(y_0) = \log A(\kappa) + (\widetilde{\theta} - 1) \log y_0.$$

Differentiating it in κ gives

$$\epsilon_L(y_0)\, \frac{\partial \log y_0}{\partial \kappa} = \epsilon_{\lambda,\kappa} + (\widetilde{\theta} - 1) \frac{\partial \log y_0}{\partial \kappa},$$

where, by (D.13) and Lemma D.1(a),

$$\epsilon_{\lambda,\kappa} \equiv \frac{A'(\kappa)}{A(\kappa)} = \frac{\widehat{k}(1-\kappa)}{R_H(1-\kappa)+R_H(1)} > 0.$$

Hence

$$\frac{\partial \log y_0}{\partial \kappa} = \frac{\epsilon_{\lambda,\kappa}}{S_0} > 0.$$

Proof of Part (ii) and (iii): higher irreversibility raises the elasticities of the price and the markup to φ. By the proof of Proposition 2.1, with $\epsilon_\lambda(y_0) = 1 - \widetilde{\theta}$,

$$\frac{\partial \log p_0}{\partial \log \varphi} = \frac{1}{\eta S_0},$$
$$\frac{\partial \log \mu_0}{\partial \log \varphi} = \frac{\varsigma}{S_0}.$$

The parameter κ enters S_0 only through y_0, via ω_0. Since $mr_0(y)/mc_0(y) \propto y^{-\varsigma}$,

$$\frac{d\omega_0}{d \log y_0} = \varsigma(1-\omega_0),$$
$$\frac{dS_0}{d\omega_0} = -\frac{\varsigma}{\omega_0^2}.$$

By part (i),

$$\frac{\partial S_0}{\partial \kappa} = \frac{dS_0}{d\omega_0}\frac{d\omega_0}{d \log y_0}\frac{\partial \log y_0}{\partial \kappa} = -\frac{\varsigma^2(1-\omega_0)\epsilon_{\lambda,\kappa}}{\omega_0^2 S_0} < 0.$$

Therefore

$$\frac{\partial^2 \log p_0}{\partial \kappa\, \partial \log \varphi} = -\frac{1}{\eta S_0^2}\frac{\partial S_0}{\partial \kappa} = \frac{\varsigma^2(1-\omega_0)\epsilon_{\lambda,\kappa}}{\eta\, \omega_0^2 S_0^3} > 0,$$

and

$$\frac{\partial^2 \log \mu_0}{\partial \kappa \, \partial \log \varphi} = \eta\varsigma \, \frac{\partial^2 \log p_0}{\partial \kappa \, \partial \log \varphi} > 0.$$

□

E Adding Inventories to the Model

This appendix adds inventories to the model of Section 2. I set up the model and state the main results. I relegate technical details and proofs to Supplementary Appendices S5 and S6.

E.1 Setup

In $t = 0$, the firm sells its output as a continuum of parts whose demand is subject to taste shocks, as in Wen (2011). Unsold output becomes inventory that is then sold in the morning of $t = 1$ at an exogenous price p^m. Production in $t = 1$ still only occurs in the afternoon. To simplify, I assume the firm does not start with any inventories on hand in $t = 0$. Thus, if the $t = 0$ price p_0 falls when φ increases, then it results from the firm accumulating fewer inventories and not from liquidation of existing inventories on hand. Nonetheless, including inventories on hand at the start of $t = 0$ should not qualitatively change this model's implications. It should only weaken the conditions under which a firm prefers cutting prices instead of hiking to deal with an increase in φ.

Inventories. The final good sold by a firm is a CES aggregate of different parts, each of which gets an i.i.d. taste shock. For example, the final good may come in different colors, and in every period, demand for specific colors will be higher. A firm now uses capital and labor to produce each part using an identical Cobb-Douglas production technology. I make

the timing assumption that firms choose their production plans before they observe the taste shocks. As Wen (2011) proves, the firm optimally chooses their price and a cutoff value for the taste shock such that all parts with demand higher than this cutoff will get stocked out, and parts with lower demand will have goods remaining on the shelves that are stored as inventory. Using this cutoff, it is possible to write output sold and inventory accumulated in "aggregate" terms without tracking the identities of the stocked-out and inventoried parts. Supplementary Appendix S6 provides more detail.

Define q as output *produced* by the firm. Since the firm does not start with any inventories, the stock of goods on the shelf in $t = 0$ comes entirely from production. Let x_n^* be the cutoff value for the i.i.d. taste shocks, y the amount of output sold, and n the stock of inventories accumulated into the morning of $t = 1$. Supplementary Appendix S6 shows that there exist functions $\widetilde{\mathcal{Y}}(x_n^*)$ and $\widetilde{\mathcal{N}}(x_n^*)$ such that $y = \widetilde{\mathcal{Y}}(x_n^*)q$ and $n = \widetilde{\mathcal{N}}(x_n^*)q$. Further, for a given y, there is a one-to-one mapping between n and x_n^*. The chosen cutoff uniquely determines the stock of accumulated inventories. The cost of production in $t = 0$ now depends on n as well. I suppress the dependence on the initial capital stock with the notation $\widetilde{C}(y, n) \equiv C\big(q(y, n), k_0\big)$.

A fraction $\delta_n \in [0, 1)$ of the stock left unsold at $t = 0$ depreciates. The firm can sell the remainder in the morning of $t = 1$ at the price $p^m > 0$. The different parts become perfect substitutes in the morning market. Morning sales also do not affect the customer base. These sales happen because there exists a continuum of perfectly competitive markets for each part. Because the parts are all produced with identical technologies, they sell for the same price across markets. No customer base is built because the firm is selling the individual inventories, not its final good. The firm still behaves as a monopolist for its own good because the aggregation of the different parts into the final good differentiates the parts.

This modeling approach to inventories makes three stylized assumptions. First, the

firm does not get to sell inventories in the afternoon of $t = 1$. Second, inventory sales in the morning do not affect the customer base. Third, the firm gets to treat inventories as substitutes and sell at an exogenous price p^m. I make the first two assumptions because the point of inventories is primarily to give firms a reason to cut prices after an increase in the marginal value of liquidity φ. I do not introduce inventories to study interactions between the customer-market motive and inventory choices. By requiring inventories to be sold in the morning instead of the afternoon and assuming away an effect of morning sales on the size of the customer base, I prevent excessive interactions between customer markets and inventories. Otherwise, it becomes difficult to obtain analytical results with this microfoundation of inventories.[56] The third assumption simplifies the characterization of the incentive to hold inventories. Because my model has a finite horizon, the firm optimally dumps all inventories in the last period of sales. However, that means equal amounts of on-the-shelf goods may not be optimal under some parameters since some parts will have stocked out, and it may not be optimal to fully replenish those parts. It is not economically interesting to establish the precise parameters under which equal amounts of on-the-shelf goods is optimal or to account for the effects on the inventory incentive when the firm cannot offer equal amounts of on-the-shelf parts in the morning of $t = 1$. The infinite-horizon version in Wen (2011) avoids this issue because the problem is recursive there.

The Objective. The firm's objective can be written as

$$\begin{aligned} J(y,n) &\equiv \varphi\big[y^{1-1/\eta} - \widetilde{C}(y,n)\big] + bn + \mathcal{V}(y), \qquad \text{(E.1)} \\ b &\equiv \frac{(1-\delta_n)p^m}{R}, \\ \mathcal{V}(y) &\equiv \frac{1}{2R}\sum_{z\in\{B,G\}} T\big(\mathcal{H}(y \mid z);\kappa\big). \end{aligned}$$

[56] I could probably write down reduced-form functions for how inventories affect output sold to get analytical results. However, the current approach is simpler and clearer about the role of inventories since they have limited interactions with customer markets by assumption.

As in Appendix D, I can define the marginal loss and write it normalized by the marginal cost as

$$L(y,n) \equiv \widetilde{C}_y(y,n) - mr_0(y),$$
$$\omega(y,n) \equiv \frac{L(y,n)}{\widetilde{C}_y(y,n)}.$$

At an optimum with $n_0 > 0$, the first-order conditions are

$$\varphi\, L(y_0,n_0) = \lambda(y_0), \tag{E.2}$$
$$\varphi\, \widetilde{C}_n(y_0,n_0) = b. \tag{E.3}$$

Since $mr_0(y_0) = \frac{\eta-1}{\eta}p_0$, (E.2) is the price equation (3) with $\widetilde{C}_y$ in place of mc_0. To ensure the analysis is not moot, I assume parameters are such that $n_0 > 0$ is optimal. In Supplementary Appendix S5.4, I establish these conditions.

E.2 Statements of the Inventory Results

I defer the proofs to Supplementary Appendix S5.3 and state the key results here.

Proposition E.1. *Assume that the demand states B and G are far apart, κ is small, and χ is small relative to k_0, so that the firm sells capital in the morning of the $t = 1$ bad state and buys capital in the morning of the $t = 1$ good state. Also assume that the value of morning sales from inventories is sufficiently high, the customer-market incentive is not too strong, and the cost of production is sufficiently convex. Then the following claims are true.*

(i) If the inventory incentive is stronger than the customer-market incentive, then its log price and inventory accumulation fall: $\dfrac{\partial \log p_0}{\partial \log \varphi} < 0$ *and* $\dfrac{\partial \log n_0}{\partial \log \varphi} < 0$.

(ii) A firm with higher irreversibility invests more in the customer base and has a higher

elasticity of its price to φ:

$$\frac{\partial \log y_0}{\partial \kappa} > 0, \quad \frac{\partial^2 \log p_0}{\partial \kappa \, \partial \log \varphi} > 0.$$

(iii) For a sufficiently strong effect of y_0 on the customer base, $\theta < -1/\eta$, the elasticity of the markup of the price over output sold to φ also increases with κ.

Note that the requirement of $\theta < -1/\eta$ in part (iii) is compatible with the broader requirement that the customer-market incentive is not too strong because χ can be smaller to ensure a weak enough overall customer-market incentive.

F Results from the Two-Industry DSGE

This section shows that general equilibrium attenuates the increase in price rigidity when there is a difference in the customer-market incentive across industries. The reason is that monetary policy responds to adverse credit supply shocks with a lower real interest rate. When the customer-market incentive is stronger in some industries, prices fall by less so the real interest rate endogenously falls by less, which changes firms' incentives to adjust prices.

Below, I give a brief overview of the model, decompose the inflation response into direct and indirect effects, and discuss how the real interest rate channel attenuates the additional rigidity from differences in the customer-market incentive.

F.1 Overview of the Quantitative Model

I briefly summarize the model and report the full details in Supplementary Appendix S8. The model is a two-industry DSGE. The two industries are identical except that firms in industry 1 have non-pecuniary value for the customer base. Firms in industry 2 have no such value. In both industries, firms hold inventories, face an earnings binding constraint,

and have quadratic dividend adjustment costs. These ingredients allow me to simulate credit supply shocks in the model and calibrate it to the empirical evidence. To simplify the calibration, the model's time frequency is annual rather than quarterly and matches the year-over-year price response. The difference in responses identifies θ_f, which indexes industry 1's non-pecuniary value for a larger customer base.[57] I also allow for mild deep habits on the household side, in line with the model in Section 2, where goods-specific habits are needed to make customer acquisition valuable for high-irreversibility firms.

I add nominal rigidities to the model so that we can study the implications for inflation. Prices and wages are both sticky due to Rotemberg costs. I calibrate the costs to match a 9.5% monthly frequency of price changes and an average duration of time between wage changes of 6 quarters, following Nakamura and Steinsson (2008) and Grigsby et al. (2021). The price stickiness is relatively mild because firms operate in customer markets, and I calibrate to the micro-evidence instead of estimates of the aggregate Phillips Curve, such as Hazell et al. (2022). The central bank follows a standard Taylor rule with persistence in the nominal rate and penalties for deviations from the inflation targets.

F.2 Impact of An Aggregate Credit Supply Shocks on Inflation

The Missing Intercept. After a credit supply shock that lowers aggregate debt by 1%, impact inflation is -1.29% in the economy with differences in the customer-market incentive and -1.59% in a counterfactual economy in which both industries have weak customer-market incentives because I shut off the non-pecuniary value for the customer base. Irreversibility therefore dampens the impact response by 19.2%, where I define the dampening as $1 - C_1/C_2$ with C_1 the baseline economy and C_2 the counterfactual response.

The micro difference-in-differences evidence alone implies a much smaller response of

[57] In reality, there may be differences in other characteristics between high and low irreversibility industries that influence the relative difference in price changes, such as their inventory technology. For parsimony and to focus on the customer-market incentive, I assume θ_f is the sole source of differences.

inflation to a credit supply shock. Inside the model, the difference-in-differences slopes imply an aggregate effect of roughly -0.40% in the economy with differences in the customer-market incentive and -0.60% in the counterfactual economy per 1% fall in debt, compared with the model responses of -1.29% and -1.59%. These differences indicate a large negative missing intercept, at least within this DSGE.[58]

To investigate the role of different general-equilibrium channels, I decompose the impact response of inflation into direct and indirect effects. I compute the direct effect by taking the firm's linearized partial-equilibrium block and solving the implied inflation response to an aggregate credit supply shock, holding fixed all endogenous aggregate variables. I compute the indirect effect of a given channel by feeding in the channel's equilibrium aggregate paths into the firm block and differencing out the direct effect. The channels I consider are the nominal wage channel (Π_w), aggregate demand channel (p_X, X, and I), and the real interest rate channel (R).[59] The wage channel amplifies the inflation response ($-0.53\,\%$ in the economy with differences in the customer-market incentive and $-0.63\,\%$ in the counterfactual economy) because production cuts by firms result in lower equilibrium labor supplied, which pushes wages down. The demand channel mitigates the fall in inflation ($0.26\,\%$ and $0.27\,\%$) because the fire sale of inventories in $t = 0$ incentivizes temporarily higher demand, and that higher demand increases firms' desired prices. The real interest rate channel amplifies the inflation response (-0.09) in the economy with differences in the customer-market incentive but dampens the response (0.06) in the counterfactual economy. Monetary policy endogenously lowers the real interest rate in my model (there is no zero-lower bound). When firms in industry 1 have strong customer-market incentives, a lower real rate incentivizes firms

[58] See Wolf (2021) for an extensive discussion of the missing intercept problem.

[59] The real interest rate is directly linked to aggregate demand by the Euler equation. The decomposition presented here is about the direct effects of the paths of equilibrium aggregates on the firm block's decisions, not necessarily how those aggregates get determined in equilibrium. The small effect of the interest rate channel here simply signifies that movements in the real rate do not affect the firm's price decision directly by much. Instead, the real rate affects the firm's price indirectly through wages and aggregate demand.

to partially undo their disinvestment from their customer base, which pushes prices down. When the two industries are identical, firms instead respond to a lower real rate by holding onto more of their inventories, which mitigates the decline in prices.

In the DSGE, heterogeneity in the customer-market incentive increases price rigidity by less because monetary policy implements a lower real interest rate. In the model, prices are more rigid by 19.2% compared to the predicted increase in rigidity by 33.2% based on the diff-in-diff estimates within the model. The predicted increase based on the direct effect has a comparable magnitude to the main text's back of the envelope calculation. The indirect effect, however, makes prices more flexible in the economy with differences in the customer-market incentive and makes prices more rigid in the counterfactual economy, which shrinks how much rigidity occurs because of the customer-market incentive. If we ignore the real interest rate channel in both economies, then prices are more rigid by 27.5%, which is much closer to the rigidity implied by the model's diff-in-diff of 33.2%.

Comparison to the Back-of-the-Envelope. The dampening due to an asymmetry in the customer-market incentive does not map directly to the main text's back-of-the-envelope calculation. The magnitude of the credit supply shock was normalized to one in the previous part, and the average credit supply shock for high-irreversibility industries is slightly smaller in the back-of-the-envelope calculation, so a symmetric aggregate shock is not a perfect match. Since this DSGE has just two industries, I also recompute the back-of-the-envelope using the coefficient estimates from the regression with an above/below median irreversibility indicator for the interaction. The back-of-the-envelope calculation suggests that prices are more rigid by 31.4% when some industries have more irreversible investment. For the DSGE, this number becomes 16.0%. As I discussed previously, general equilibrium attenuates the reduction in rigidity because the indirect effects of the credit supply shock do not shrink by as much as the direct effect. If we turn off the real interest rate channel, then the increase

in rigidity becomes 24.7%.

F.3 Reduced-Form Modeling Device for Difference in Customer-Market Incentives

This section explains how I generate a difference in the customer-market incentive across industries with a reduced-form modeling device. The device imitates (relative) deep habits from Ravn et al. (2006) but instead supposes firms have customer-specific "habits".

Setup. Firms are indexed by f and households by $j \in [0,1]$. The relationship between firm f and household j is measured by the habit stock $h_{f,j,t}$, which follows

$$h_{f,j,t} = \rho_h \, h_{f,j,t-1} + (1-\rho_h)\, c_{f,j,t}, \qquad h_{f,t} \equiv \int_0^1 h_{f,j,t}\, dj. \tag{F.1}$$

Firm f charges a household-specific price $p_{f,j,t}$

$$c_{f,j,t} = p_{f,j,t}^{-\eta}\, \mathcal{H}_h \, h_{f,j,t-1}^{\theta(1-\eta)}, \qquad \eta > 1,\ \theta \leq 0. \tag{F.2}$$

Customer-Specific Habits. To give firm f a value for specific customers, I imitate deep habits from Ravn et al. (2006) and assume that the firm is operated by a manager who maximizes the present discounted value of dividends *plus* an additional preference over the flow of sales to each household j given by

$$v_{f,t} \;=\; \left(\mathcal{V}_{f,t} - \mathcal{V}_{f,t}|_{\theta_f=0}\right). \tag{F.3}$$

where

$$\mathcal{V}_{f,t} = \left[\int_0^1 \left(c_{f,j,t} \left(\frac{h_{f,j,t-1}}{\overline{h}_{j,t-1}} \right)^{-\theta_f} \right)^{\frac{\eta_f - 1}{\eta_f}} dj \right]^{\frac{\eta_f}{\eta_f - 1}}, \quad \theta_f \leq 0, \eta_f > 1 \tag{F.4}$$

$$\mathcal{V}_{f,t}|_{\theta_f = 0} = \left[\int_0^1 c_{f,j,t}^{\frac{\eta_f - 1}{\eta_f}} dj \right]^{\frac{\eta_f}{\eta_f - 1}}, \tag{F.5}$$

$$\overline{h}_{j,t-1} = \int_{f'} h_{f',j,t-1} \, \mathrm{d}f'. \tag{F.6}$$

The firm's non-pecuniary flow payoff $v_{f,t}$ is the difference between an aggregator with habits and that same aggregator with the habit parameter θ_f set to zero. I choose this functional form so that, when $\theta_f = 0$, the firm derives zero additional payoff from its customer relationships. Unlike the household side, the habit adjustment is relative to the average habit stock of household j across all firms, $\overline{h}_{j,t-1}$, which firm f takes as given since it is atomistic. The reason for $\overline{h}_{j,t-1}$ is that I want the functional form to mathematically resemble the effects of the household's deep-habits on the firm's pricing incentives. The household always evaluates the marginal utility of another purchase from a particular firm relative to the marginal utility from other firms. Without $\overline{h}_{j,t-1}$, the firm does not evaluate the "utility" of sales to one customer relative to the sales it makes to other customers. Aside from this mathematical requirement, it is plausible that a firm evaluates the importance of investment in specific customers based on what their competitors are doing. If all their competitors have been investing in a relationship with household j, then they also want to invest in a relationswhip with household j.

The firm's objective function becomes

$$\mathbb{E}_0 \sum_{t \geq 0} M_{0,t} \left[d_{f,t} \; + \; v_{f,t} \right]. \tag{F.7}$$

Aggregated Form. In my model, households are identical, so a symmetric equilibrium generically exists in which each firm has the same habit stock with respect to each household, $h_{f,j,t} = h_{f,t}$. Then (F.3) reduces to the functional form

$$v\left(c, h, \overline{h}\right) \equiv c\left[\left(\frac{h}{\overline{h}}\right)^{-\theta_f} - 1\right], \tag{F.8}$$

so that $v_{f,t} = v(c_{f,t}, h_{f,t-1}, \overline{h}_{f,t-1})$. The two key partial derivatives are

$$v_c\left(c, h, \overline{h}\right) = \left(\frac{h}{\overline{h}}\right)^{-\theta_f} - 1, \tag{F.9}$$

$$v_h\left(c, h, \overline{h}\right) = -\theta_f \frac{c}{h}\left(\frac{h}{\overline{h}}\right)^{-\theta_f}, \tag{F.10}$$

When firms are also symmetric, these derivatives simplify to

$$v_c(c, h, h) = 0, \quad v_h(c, h, h) = -\theta_f \frac{c}{h}, \tag{F.11}$$

hence the firm derives no additional value directly from another sale but does value a larger habit stock. The fact that $v_c = 0$ mirrors the fact that, with goods-specific habits, a firm does not value sales to households depending on a household's level of consumption, only because the household has a habit stock for that firm. This zero is precisely why I need the external benchmark.