

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

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Abstract

This paper argues that investment irreversibility in tangible capital leads to greater output price rigidity. The mechanism is that irreversibility strengthens the customer-market incentive: selling more output today builds a sticky customer base, which insures against bad shocks to future demand. Greater ex-ante investment in the customer base then leads a firm to choose higher price changes when financial constraints tighten. These higher price changes make markups more countercyclical and thereby increase output price rigidity. To show that this connection is empirically relevant, I use the bankruptcy of Lehman Brothers as a natural experiment in the credit supplied to firms and find that, while firms in industries with low irreversibility cut prices, firms in industries with high irreversibility do not. Abstracting from general equilibrium effects, aggregate prices are almost 40% more rigid after reductions in credit supply than if all industries had low irreversibility.

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1 Introduction

Inflation comoves with aggregate output. The strength of this relation depends, in part, on the degree of price rigidity. The more rigid that prices are, the less that 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 will accumulate sticky customer bases by lowering prices to sell more output because customers prefer to buy from the same firm over time.¹ Customer markets can create real price rigidity by making markups more countercyclical.² How strong, then, is the effect of the customer-market incentive on price rigidity? What mechanisms amplify the strength of the customer-market incentive?

This paper argues that investment irreversibility in tangible capital strengthens the customer-market incentive and thereby makes prices more rigid. Irreversibility amplifies the costs of bad idiosyncratic demand shocks in the future, so if a customer base generates more predictable demand, then firms will insure against bad future demand shocks by investing in a larger customer base. This greater investment in the customer base, however, leads to more higher price and markup responses after increases in the marginal value of internal liquidity in the present. I find empirical support for this hypothesis when I compare how firms adjust prices after credit supply shocks in industries with high versus low irreversibility.

My analysis begins with a simple two-period partial-equilibrium model to explain why firms with more irreversible investment have a stronger incentive to accumulate a sticky

¹See 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 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.

²There is empirical evidence that markups are countercyclical, although recent research is conflicted. While Bils et al. (2018) shows that sectoral markups are countercyclical with respect to aggregate output, Nekarda and Ramey (2020) finds procyclical or acyclical sectoral markups with respect to sectoral output, conditional on demand shocks. More recent papers by Burstein et al. (2025) and Chiavari et al. (2025) suggest that differences in aggregation can affect the sign of the cyclicity, and Blampied and Mahadeo (2025) finds that markups may be countercyclical in recessions but procyclical in expansions.

customer base. Investment is partially irreversible because the firm must sell capital at a lower price than the purchase price. This irreversibility wedge penalizes the firm if the firm sells capital in the future after a bad demand shock. A sticky customer base mitigates this problem when demand from the customer base is predictable and not subject to shocks. If the customer base makes up a larger share of a firm's future demand, then the firm faces effectively lower demand risk, which reduces future capital sales after bad shocks and the associated losses from irreversibility.

Because firms with higher irreversibility invest more in their customer base out of concern about future demand shocks, their prices and markups become more sensitive to increases in the marginal value of internal liquidity today due to tighter financial constraints. The reason is that firms in a customer market acquire their marginal customer at a loss. If irreversibility strengthens the customer-market incentive, then more irreversible firms acquire the marginal customer at a greater loss. After an increase in current liquidity demand, firms with greater investment in the customer base will cut their losses more aggressively with larger hikes in prices and markups. This result applies more broadly to any reason that causes the effective discount rate to increase, but I focus on liquidity demand shocks because empirically other discount rate shocks like monetary policy shocks may have low statistical power compared to variation in financial constraints. While this link between financial constraints and countercyclical markups in customer markets has been articulated previously by [Gottfries \(1991\)](#), [Chevalier and Scharfstein \(1996\)](#), and [Gilchrist et al. \(2017\)](#), my paper contributes the novel point that irreversibility amplifies this link. Finally, the key prediction of the model is that price changes are relatively higher for more irreversible firms. The actual sign of the price response to higher liquidity demand can be negative due to, for example, inventory liquidation.

It is also important to note that this paper's argument is not about the *ex-post* interaction of irreversibility and prices after the realization of a bad idiosyncratic demand

shock. This paper argues for an *ex-ante* interaction in the sense that irreversibility leads to greater ex-ante investment in the customer base because firms anticipate bad idiosyncratic demand shocks *in the future*. Greater ex-ante investment changes how prices adjust *today* after current, not future, shifts in the marginal value of internal liquidity.

In support of the idea that irreversibility strengthens the customer-market incentive, I show that the irreversibility of tangible capital at the industry level is associated with two proxies for investment in sticky customer bases: the average duration of firm-to-firm contracts and selling expenses as a share of sales. I measure investment irreversibility using estimates from [Kermani and Ma \(2023\)](#) of the predicted recovery rate of tangible capital based on physical attributes. [Kermani and Ma \(2023\)](#) shows that this measure can be interpreted as a proxy for investment irreversibility because firms sell capital less frequently and cut their investment rates by more in response to an uncertainty shock when they operate in industries with lower predicted recovery rates. The duration of firm-to-firm contracts is a proxy for investment in a sticky customer base because longer contracts lock in customer demand further into the future and gives firms more predictability about their future demand.³ Selling expenses are another proxy because firms can also use marketing or salespeople to acquire customers.⁴ However, this evidence is only descriptive and does not directly show that prices adjust differently in more irreversible industries.

For direct evidence on the relationship between irreversibility and price setting, I use the bankruptcy of Lehman Brothers as a source of quasi-random variation in the credit supplied to firms and find that, while firms in industries with less irreversible investment cut year-over-year prices by 10% in 2009:Q3, firms in industries with more irreversible investment

³Across multiple industries, long-term contracts or contracts with longer durations have been used to mitigate frictions due to demand uncertainty or relationship-specific investments, such as upfront sunk costs that originate from investment irreversibility on tangible capital or other frictions. Examples include energy markets ([Joskow 1987](#), [Von Hirschhausen and Neumann 2008](#), and [Zahur 2026](#)), trucking ([Hubbard 2001](#)), and pulp and paper ([Darmouni et al. 2026](#)).

⁴See [Gourio and Rudanko \(2014\)](#), [Peters and Taylor \(2017\)](#), [Gilchrist et al. \(2017\)](#), and [Chiavari \(2026\)](#).

do not cut prices. Thus, firms in industries with higher irreversibility choose higher price changes relative to firms in industries with lower irreversibility, consistent with my model’s prediction. I measure exogenous and firm-specific credit supply shocks using the heterogeneous exposure of banks in the syndicated loan market to the bankruptcy of Lehman Brothers following [Chodorow-Reich \(2014\)](#) and [Kim \(2021\)](#), and I measure quality-adjusted prices using price microdata from the Bureau of Labor Statistics’s (BLS) Producer Price Index (PPI) survey. These results are not specific to this sample; I find similar difference in the impact of credit supply shocks on export unit-value prices constructed from the Longitudinal Firm Trade Transactions Database (LFTTD). To support customer markets as the reason for these results, I show that markups are also temporarily higher in industries with greater irreversibility. Abstracting from general equilibrium effects, a back-of-the-envelope calculation suggests that aggregate prices in the US during the Global Financial Crisis were nearly 40% more rigid than if all industries had low irreversibility.

Related Literature. This paper’s primary contribution is that investment irreversibility strengthens the customer-market incentive and thereby makes prices more rigid. To the best of my knowledge, this paper is the first to theoretically propose an interaction between irreversibility and customer markets as well as the first to provide empirical evidence that prices adjust differently in industries with higher irreversibility after plausibly exogenous shocks. [Kermani and Ma \(2023\)](#) provides descriptive evidence that higher irreversibility is associated with stickier prices and connect this empirical result to [Altig et al. \(2011\)](#)’s theoretical finding that firm-specific capital decreases the magnitude of desired price changes. In contrast, this paper provides evidence that the customer-market incentive may explain this relationship. Prices are stickier because customer markets generate countercyclical markups.⁵ Irreversibility may also influence output prices because it affects borrowing constraints, which

⁵Section 4.3 discusses at length why customer markets is arguably a more plausible explanation than the mechanism in [Altig et al. \(2011\)](#).

shape the level and dispersion of markups across firms according to [Li et al. \(2025\)](#). Relative to the broader literature on customer markets and price setting, this paper contributes a novel mechanism that strengthens the customer-market incentive.

A secondary but important contribution is causal evidence which reconciles conflicting results in the literature about how prices respond to tighter financial constraints. [Chevalier and Scharfstein \(1996\)](#), [Gilchrist et al. \(2017\)](#), [Christiano et al. \(2015\)](#), and [Berardi \(2024\)](#) show that tighter financial constraints can 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. \(2026\)](#) validate these channels using plausibly exogenous variation in credit supply. However, [Kim \(2021\)](#) and [Lenzu et al. \(accepted\)](#) also use plausibly exogenous variation in credit supply but find that prices tend to *fall*, not rise, in the short run due to the fire sale of inventories. To explain the difference in signs, [Renkin and Züllig \(2024\)](#) suggests that firms in its sample did not have significant inventory holdings. My results confirm that tighter financial constraints can lead to price hikes or cuts, but I use a novel mechanism to generate variation in the relative importance of the customer-market incentive versus the inventory incentive. These results also relate to research on state-dependent sensitivity of inflation to output fluctuations due to financial frictions, such as [Acharya et al. \(2026\)](#), [Drechsler et al. \(2026\)](#), and [Liu \(2026\)](#).

Aside from these two contributions, this paper belongs to the large literature on how input adjustment costs affect firm behavior. [Bernanke \(1983\)](#), [Abel and Eberly \(1996\)](#), and [Abel and Eberly \(1999\)](#), among many other papers, theoretically study how investment irreversibility creates an option value to waiting to invest. Micro-level irreversibility also affects macroeconomic outcomes by smoothing investment dynamics ([Bertola and Caballero \(1994\)](#)) and increasing the persistence of capital fluctuations ([Baley and Blanco \(2026\)](#)). Empirically, [Cooper and Haltiwanger \(2006\)](#) and [Bai et al. \(2024\)](#) find that irreversibility is an important characteristic of micro investment behavior, and, consistent with a real

options channel, positive idiosyncratic uncertainty shocks reduce firm-level investment rates (Gilchrist et al. (2014) and Alfaro et al. (2024)). Other sources of input adjustment costs include fixed costs, which generate lumpy behavior (Caballero and Engel (1993), Abel and Eberly (1994), Caballero and Engel (1999), Bloom (2009), Khan and Thomas (2013), Bloom et al. (2018), Winberry (2021), Melcangi (2024)), search frictions that turn labor into a partially irreversible investment which responds to fluctuations in discount rates or risk premia (Hall (2017), Kehoe et al. (2022), Meeuwis et al. (2025)), and organizational or planning frictions (Selgrad and Siani (2025)).

Outline. Section 2 uses a partial equilibrium model to explain why firms value a sticky customer base when they face irreversible investment in tangible capital and how irreversibility affects the price response to shifts in the marginal value of internal liquidity. I describe the data and empirical methodology for testing this model’s predictions in Section 3 followed by the results in Section 4. Finally, Section 5 quantifies the importance of this mechanism using a back-of-the-envelope calculation.

2 Irreversibility and Customer Markets

This section presents a stylized two-period partial-equilibrium model which shows that when irreversibility amplifies the cost of bad future demand shocks, firms have a stronger *ex-ante* customer-market incentive because a larger customer base insures against low demand *ex-post*. As a result, higher irreversibility leads firms to choose higher price changes when financial constraints tighten *before* demand uncertainty resolves. Omitted derivations are in Appendix E.

2.1 Setup

This subsection only sets up the model. I will discuss the assumptions of the model when I analyze the model's implications.

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 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 to be the primary source of concern instead of aggregate risk when it comes to the costs of investment irreversibility because micro uncertainty is far larger than macro uncertainty for most firms.

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 in 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.

Customer Demand. In both periods, the firm faces a demand curve with intratemporal elasticity of demand $\eta > 1$. However, the amount of demand for a given price is not the

same across time. Specifically, the firm sells output y_t and a price p_t according to

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

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.⁶ 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 are customers who signed long-term contracts. To acquire customers into long-term contracts, the firm needs to set lower prices in $t = 0$.

Objective of the Firm. The firm maximizes the objective

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

⁶According 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.

where 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 because tighter constraints across many different specifications result in a higher φ .⁷

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 higher price changes if financial constraints tighten 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. Now, let me discuss some key assumptions of the model and justify them as economically reasonable.

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 capital sales 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

⁷Specific models of financial constraints may also lead to Lagrange multipliers that distort other decisions, holding fixed φ . For example, a working capital constraint on labor would specifically increase the effective cost of labor, not just all costs in general.

want to make any adjustment to its capital stock due to large fixed costs. For these reasons, I think it is not that problematic of an assumption to only allow the capital stock to adjust in $t = 1$.

Another key assumption of the model is that 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.⁸ While the expected return on capital still rises with a larger customerbase, exposure to the idiosyncratic demand shock also rises so that a bad demand shock is larger in magnitude. In contrast, exposure to the demand shock falls with a larger customer base when I use the additive form, which is a better fit for the idea that customer bases provide predictable demand.

In the analysis below, I focus exclusively on shifts in φ , the marginal value of internal liquidity, but these shifts are essentially just discount rate shocks. In other words, any shock to the discount rate in my model would lead to the same result. Like customer market models, such as [Ravn et al. \(2006\)](#), my model of customer markets generates countercyclical markups precisely because changes in discount rates adjust a firm’s incentive to invest in their customer base. However, when I go to the data to provide empirical evidence on the interaction between investment irreversibility and customer markets, I will use credit supply shocks during the Global Financial Crisis. These shocks generate substantial variation in firms’ effective discount rates, which helps with identifying the mechanism. In contrast, monetary policy shocks may be too small to detect the interaction empirically. I return to this point in [Section 3.3](#).

⁸[Dou et al. \(2021\)](#) model 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.

Connection to Price Rigidity. This model has a *real* price rigidity, not a nominal rigidity. At the firm level, prices are not literally rigid. Indeed, after an increase in the marginal value of internal liquidity φ while holding wages constant, the firm optimally chooses higher price changes and thus higher markup changes. However, wages also move in equilibrium. When an increase in φ coincides with a fall in wages, the firm's *equilibrium* price may not move very much. When placed in a general equilibrium model, this mechanism tends to make inflation less sensitive to output fluctuations.

The intuition is that the comovement of inflation with output results from procyclical marginal costs, but countercyclical markups offset procyclical marginal costs. Across a variety of models, a firm's optimal nominal price P_t will take a form similar to $P_t = \mu_t MC_t$, where μ_t is the firm's markup over its nominal marginal cost MC_t .⁹ Conditional on aggregate shocks that do not affect costs directly, the nominal marginal cost is usually procyclical in general equilibrium, so the price level falls after a decline in output, holding the markup μ_t constant. Nominal rigidities attenuate this decline because individual firms cannot cut their prices. However, a firm's nominal price could also appear more rigid if the firm optimally responds to the adverse aggregate shock with a higher markup μ_t .

For example, even if the nominal marginal cost falls by 1%, if the markup also increases by 1%, then the firm's nominal price will appear perfectly rigid. If adverse aggregate shocks simultaneously push down marginal costs and increase the marginal value of internal liquidity, then the mechanism in my partial equilibrium model should lead to more countercyclical markups and more rigid aggregate prices if it were placed inside a general equilibrium model. Note that this implication is not unique to my model. It is a feature of many customer-market models. This paper's contribution is the novel connection to irreversibility.

⁹In a model with sticky prices, the exact expression will be different, but the underlying basis for the firm's price decision still takes this form. For example, with Rotemberg adjustment costs, a firm targets $P_t = \mu_t MC_t$ but also takes into account the contemporaneous and future costs of adjusting prices.

2.2 The Price Response to Tighter Financial Constraints

This section characterizes the elasticity of prices in $t = 0$ to the marginal value of internal liquidity φ . 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. Finally, I explain that any idiosyncratic shift in a firm's discount rate would generally work as identifying variation, but I focus on credit supply shocks for statistical power.

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

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

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 $t = 0$ generates not only revenue but also brings future demand in the afternoon of $t = 1$, a firm has

¹⁰The 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.

an incentive to cut its price below the markup over marginal cost, 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 internal 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 $\log \varphi$:*

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

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 channel 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 internal 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 .

¹¹This 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, $\frac{\partial \log y_0}{\partial \kappa} > 0$, and*
- (ii) *has a higher elasticity of prices and markups to shifts in φ :*

$$\frac{\partial^2 \log p_0}{\partial \kappa \partial \log \varphi} > 0 \text{ and } \frac{\partial^2 \log \mu_0}{\partial \kappa \partial \log \varphi} > 0. \quad (5)$$

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 statement of these assumptions are provided in Appendix E.

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 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 becomes more

¹²Higher 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.

positive. When the irreversibility wedge κ increases, the firm prefers lower profits in $t = 0$ to ensure a larger customer base when demand from searchers is low. But as a result, if the firm needs liquidity in $t = 0$, then the firm will cut back on production and hike prices much more aggressively than a firm with lower irreversibility. The intuition is that the marginal sale comes at a larger marginal loss when y_0 is higher. When the value of liquidity in $t = 0$ rises, an irreversible firm finds it much more attractive to disinvest from the customer base to stop these very unprofitable sales. In contrast, a firm with low irreversibility does not get much back from cutting output in $t = 0$ compared to the losses the firm would sustain due to a smaller customer base in $t = 1$.

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 internal liquidity φ , not that prices increase with φ . 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 internal liquidity while cutting prices. Appendix ?? 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.

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 output produced and increase output sold, which pushes prices down, if the firm holds onto 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 the datasets and document key characteristics about the main sample of analysis. Then I provide descriptive evidence that irreversibility is associated with longer contracts and higher selling expenses. These associations support the idea that irreversibility interacts with customer markets in the sense that irreversibility incentivizes firms to invest in future demand. However, this descriptive evidence does not directly show that firms set prices differently in industries with higher irreversibility, as the theory predicts in Section 2. For this reason, I turn to credit supply shocks as a way to shift the marginal value of internal liquidity and study the effect on prices.

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),¹³ (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 Appendix A.1 for details on how I clean and construct this dataset.

¹³My access to the PPI microdata was indefinitely suspended as of September 2025 due to limited resources at the BLS to support external research projects.

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 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 US 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 come together as a syndicate to issue a loan. One or more banks works 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.¹⁴ 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.¹⁵ This measure

¹⁴Using 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.

¹⁵This 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.

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 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 3.3, 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 their 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.¹⁶ 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 latter two results also assuage the concern that recovery rates only predict behavior during bankruptcy and not during normal times.

I supplement the previous three data sources with balance-sheet 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

¹⁶They consider four attributes: mobility, customizability, durability, and the equipment share of capital. Mobility is measured as transportation costs divided by production costs. Customizability is measured as design costs divided by production costs. Durability is measured using depreciation rates from Compustat. Equipment shares are measured from the BEA detailed fixed asset tables.

size using the Longitudinal Business Database (LBD). Finally, I also study the behavior of export prices, markups, inventories, and capital stocks with data from the Longitudinal Firm Trade Transactions Database (LFTTD) and Annual Survey/Census of Manufactures (ASM/CMF).

Finally, to provide descriptive evidence that irreversibility is associated with greater investment in a customer base, I use data on firm-to-firm contracts and selling expenses. [Chen et al. \(2026\)](#) uses large language models to assemble a novel database of firm-to-firm contracts and their characteristics, including contract durations. A large literature (e.g. [Gourio and Rudanko \(2014\)](#), [Peters and Taylor \(2017\)](#), [Gilchrist et al. \(2017\)](#), and [Chiavari \(2026\)](#)) argues that activities related to customer acquisition compose a significant part of selling, general, and administrative (SG&A) expenses. Thus, it is common in the customer capital literature to interpret a high ratio of selling expenses to sales as an indicator that a firm invests in their customer base due to customer-market concerns.

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 an adjustment friction. The ACNielsen scanner price data in [Kim \(2021\)](#) primarily covers the food and beverage industry whereas the PPI covers many more industries, including all manufacturing industries, retail/wholesale trade, and some service industries. Since my measure of heterogeneity in irreversibility occurs at the 2-digit SIC level, my design would not be feasible using ACNielsen data. 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 there are not easily accessible estimates at the industry or firm level of input adjustment frictions. In contrast, [Kermani and Ma \(2023\)](#) provides plausible estimates of heterogeneity in investment irreversibility across U.S. industries.

Sample Characteristics. Table 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% but ranges 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 3.3. 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 to firms are not sensitive to 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 0.59.¹⁷ This moderately high correlation suggests that the pricing behavior in my sample is fairly similar to the broader economy’s.

3.2 Descriptive Evidence on Irreversibility and Customer Markets

This section 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.

Which Industries Have Irreversible Investment? Investment irreversibility varies widely within different types of industries, as shown in Figure 1. For instance, in non-durable and durable goods manufacturing, the difference in irreversibility exceeds 10pp between the

¹⁷The 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.

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

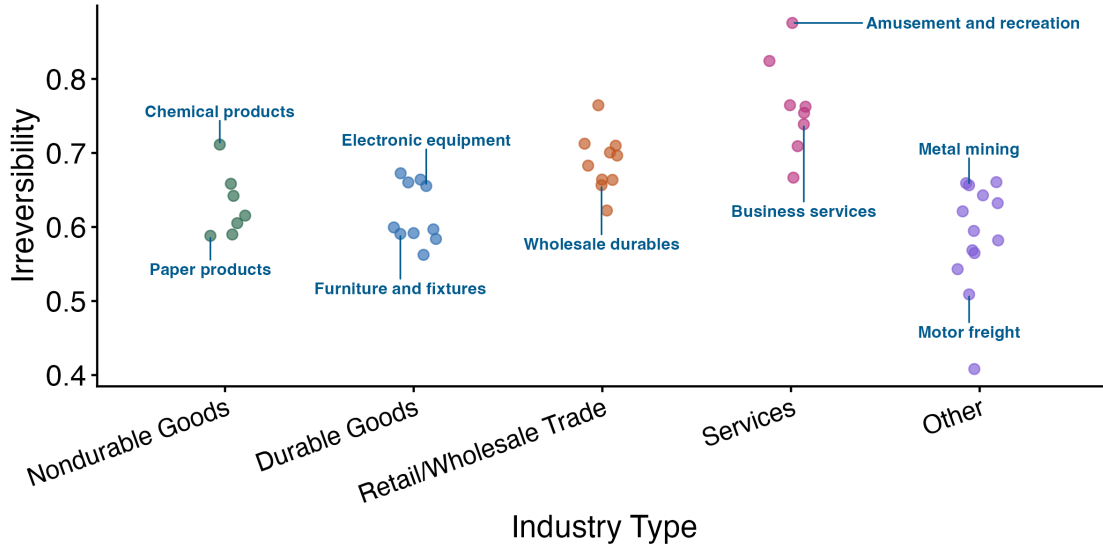
Variable	N	Mean	SD	P10	P50	P90
Public	350	0.86				
Manufacturer	350	0.57				
Bond Access	350	0.57				
Credit Supply Shock (Dealscan)	350	0.42	0.12	0.28	0.41	0.56
Lehman Co-Syndication IV (pp)	350	0.89	0.42	0.56	0.79	1.3
Employment (Mar. 2007)	350	17900	42800	724	5520	35700
Last Loan Amount (mil.)	350	711	1270	45	300	1600
Age	350	38.5	11.2	32	32	58
Irreversibility (pp)	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: 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.

most and least irreversible firms. Retail/wholesale trade and services industries generally have more irreversible tangible capital. In this paper, we should conceptualize irreversibility as the difficulty of reducing a firm’s scale rather than large upfront costs which discourage the initial investment. For example, one might suspect that, because durables manufacturing can be very capital intensive, irreversibility is higher in these industries. However, Figure 1 shows the opposite is true.

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

Figure 1: Irreversibility by Broad Industry Types



Notes: Services includes information, business/professional services, health care, education. Other combines mining, agriculture, utilities, construction, transportation/pipeline services.

their future sales. Table 2 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. \(2026\)](#).¹⁸ The positive coefficients in Table 2 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 increases the average contract duration by about a year.

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 cus-

¹⁸A 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.

Table 2: Contract Duration and Investment Irreversibility

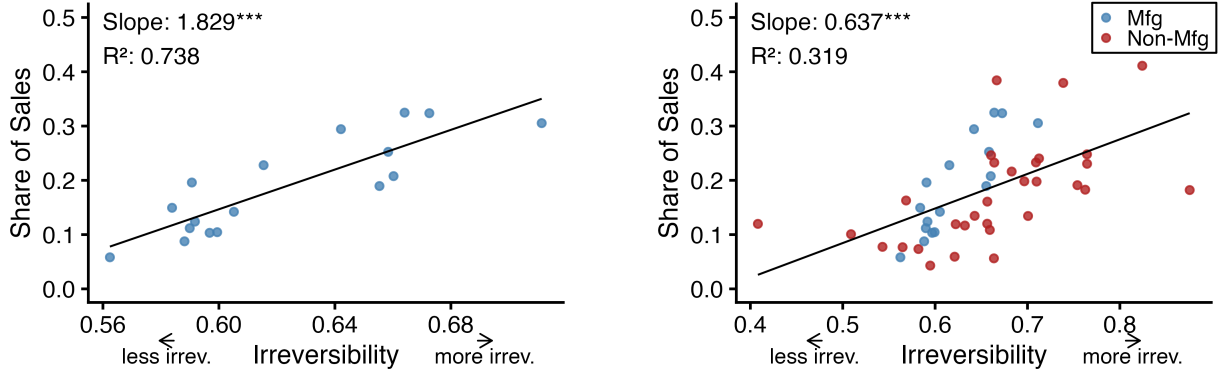
	Duration	
	(1)	(2)
Irreversibility (PLiqPPE, pp)	1.20** (0.51)	1.30** (0.49)
Include Auto-Renewals	Y	N
R^2	0.234	0.251
Industries	17	17
Contracts	908	589

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 percentage points. Robust standard errors are reported. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

toomer base. Following [Chiavari \(2026\)](#), I compute selling expenses from Compustat as $\text{Selling Expenses} = \text{xsga} - \text{xrent} - \text{xpr} - \text{recd} - \text{xrd} - \text{rdip}$. This measure takes SG&A expenses and subtracts out costs unrelated to customer acquisition.¹⁹ Figure 2 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 0.725. 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. Appendix B.1 shows that this relationship is robust across aggregation choices, definitions of the selling expenses ratio, and sample periods.

¹⁹xrent = 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 $\text{xrd} > \text{xsga}$ and $\text{xrd} < \text{cogs}$ since R&D expenses are sometimes put under COGS.

Figure 2: Selling Expenses / Sales Positively Correlate with Investment Irreversibility



(a) Manufacturing Only

(b) All Industries in [Kermani and Ma \(2023\)](#)

3.3 The Credit Supply Shock and Regression Specifications

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 internal 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 isomorphic 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

shocks series are quite small. In contrast, credit supply shocks during the Global Financial Crisis were likely both large in the magnitude of the shock to a given firm and heterogeneous across firms because some banks were much more exposed to 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, since the bankruptcy of Lehman Brothers reduced credit supply to nonfinancial firms, then 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 3 shows that this approach is consistent with the theory: industries with high irreversibility tend to have higher 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 internal liquidity φ . For this reason, I turn attention to plausibly exogenous variation in credit supplied to individual firms.

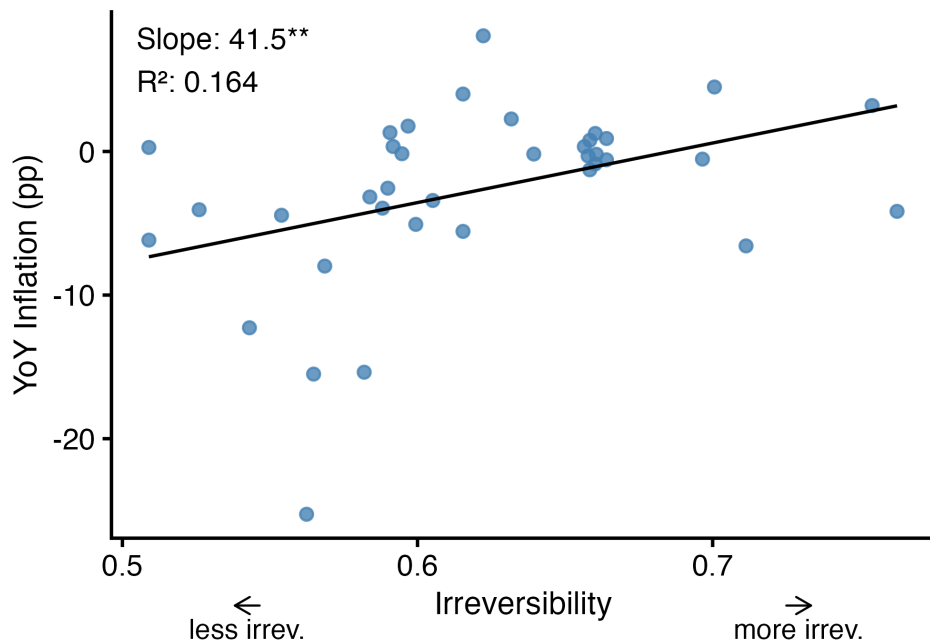
Definition of the Credit Supply Shock. I measure credit supply shocks caused by the bankruptcy of Lehman Brothers in September 2008 following Chodorow-Reich (2014). The change in bank b ’s credit supply to firm f from the pre-Lehman period to the post-Lehman period is

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

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.²⁰ A decrease in $\Delta L_{f,b}$ means that bank b has issued relatively fewer loans to firms other than f during the

²⁰The 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 .

Figure 3: Prices Fall By Less in High Irreversibility Industries After 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.

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 .²¹ Then

$$\Delta L_f = \sum_{b \in S_f} s_{f,b,\text{last}} \Delta L_{f,b} \quad (7)$$

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

²¹Many 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 \(2021\)](#).

My primary analysis instruments the credit supply shock $\Delta\tilde{L}_f$ because $\Delta\tilde{L}_f$ may not be plausibly exogenous for reason that I discuss below in Section 3.4. 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 \(2014\)](#).²² An advantage of using an instrument instead of reporting the reduced form is that the credit supply variable $\Delta\tilde{L}_f$ has more interpretable units than the co-syndication IV. The IV is a shift-share instrument: there is a *single aggregate* shift (Lehman bankruptcy in September 2008) and 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 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.²³ 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.

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

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

²²I thank Gabriel Chodorow-Reich for providing these instruments at the parent bank level on his website.

²³In Appendix D, 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.

where f is a firm, g is a product group, t is a quarter, $T = \{2007:Q3, \dots, 2009:Q3\} \setminus \{2008:Q3\}$, $H(x)$ is some function, and X_f is a set of firm characteristics measured before the Lehman bankruptcy.²⁴ 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 $\beta_{0,t}$ is identified using variation among firms within the same 3-digit NAICS industry that experience different credit supply shocks. The coefficient $\beta_{1,t}$ is identified using variation across industries in how a firm responds to the *same* credit supply 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 $\beta_{0,t}$ and $\beta_{1,t}$ describe the impact of a credit *tightening* on price changes. To address potential endogeneity of the credit supply shock, I instrument $-\Delta\tilde{L}_f$ and $-\Delta\tilde{L}_f \times H(\text{Irrev}_{\text{ind}(f)})$ with the Lehman co-syndication IV and its interaction with $H(\text{Irrev}_{\text{ind}(f)})$. I justify this strategy in Section 3.4. Because I omit 2008:Q3, $\beta_{0,t}$ and $\beta_{1,t}$ 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.²⁵

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

²⁴I 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.

²⁵Lenzu et al. (accepted) finds that clustering by primary lender leads to more conservative standard errors than the method proposed by Adão et al. (2019).

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.²⁶ I give details on the construction of $\pi_{g,f,t}$ from item-level prices in Appendix A.1.

The controls X_f account for the dynamic effects of ex-ante characteristics on price changes that could potentially pose a problem for a causal interpretation of the estimates. My choice of controls follows Chodorow-Reich (2014) and Kim (2021). The first set of controls account 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 Appendix A.1 for more details on these control variables and their construction.

²⁶Products 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.

3.4 Identification Strategy

I first justify the relevance and exogeneity of the credit supply shock and then discuss why my strategy identifies industry-level differences in the causal impact of credit supply shocks on price changes.

Relevance and Exogeneity of the Credit Supply Shock. The credit supply shock $\Delta \tilde{L}_f$ (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. \(2026\)](#)).

To make causal interpretations of the regression (8), I assume that 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 extremely 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.²⁷ 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 $\Delta\tilde{L}_f$ 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 it requires arguably 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, firm f 's bank have lent less to other firms because it 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 $\Delta\tilde{L}_f$ passes the test introduced by [Khawaja 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 C.1](#). Second, I regress observable firm characteristics on the Lehman co-syndicated instrument.²⁸ The results are reported in [Appendix C.2](#). The instrument is not correlated with most characteristics, so it

²⁷See [Chodorow-Reich \(2014\)](#) for a detailed narrative recount of the Lehman bankruptcy.

²⁸I 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 did not systematically affect certain types of borrowers.

likely reflects changes in bank health rather than firm characteristics.

Identification. The coefficients $\beta_{0,t}$ and $\beta_{1,t}$ 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 we assume that (i) a firm’s exposure to the Lehman bankruptcy due to how frequently its lenders co-syndicated with Lehman is independent of other shocks or characteristics that affect price changes, and (ii) my measure of investment irreversibility is exogenous. I have justified assumption (i). The remainder of this section discusses (ii).

My measure of irreversibility may not be exogenous because irreversibility fluctuates with aggregate and industry conditions, as [Lanteri \(2018\)](#) and [Kermani and Ma \(2023\)](#) document. Irreversibility could also be part of the treatment effect of a credit supply shock, in which case $\beta_{1,t}$ mixes the causal effect of belonging to an industry with higher irreversibility, holding the credit supply shock constant, with the change in irreversibility due to a decline in credit supply.

Nevertheless, my measure of irreversibility is not substantially affected by these endogeneity concerns for two reasons. First, my measure time-averages the recovery rate within an industry over 2000-2018, which should reduce the influence of any specific year. Second, my measure is one minus the *predicted* time-averaged recovery rate of PPE based on physical attributes measured in 1997. The causes of the financial crisis likely did not affect the measurement of these attributes because they were measured in 1997, long before the housing bubble started. Also, projecting the recovery rate onto physical attributes restricts attention to interpretable sources 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 $\beta_{1,t}$ 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, any industry characteristic correlated with irreversibility could be part of the reason for why prices adjust differently.²⁹ Caron (2025) shows that my estimate of $\beta_{1,t}$ only has a causal interpretation 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.³⁰ In the empirical analysis of Section 4.3, I perform robustness checks to explain why it is still reasonable to interpret my estimates of $\beta_{1,t}$ as evidence that irreversibility changes the response of prices to credit supply shocks.

4 Evidence from Credit Supply Shocks

The regression results in this section provide evidence in support of the hypothesis that, in normal times, irreversibility incentivizes the acquisition of a sticky customer base. Specifically, I find that firms in industries with higher investment irreversibility choose higher year-over-year (log) price changes in response to the same credit supply shock. When firms have invested more ex-ante in their customer bases by selling more output, higher price changes are an attractive way to raise internal liquidity today because the marginal sale occurs at a larger loss.

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 prices responses to credit supply shocks.

²⁹As an example, Chen et al. (2023) estimates the causal effect of a change in partial irreversibility on investment using a VAT reform in China.

³⁰Caron (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 a difficult task and out of this paper's scope.

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.

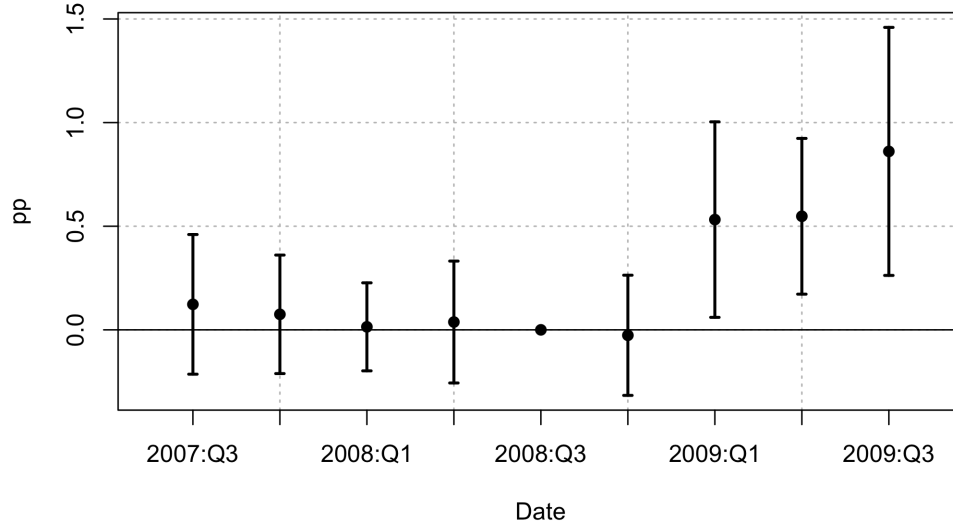
4.1 Irreversibility and the Price Responses to Credit Supply

In response to the same 1 standard deviation cut in credit supply, firms in industries with 1pp higher irreversibility choose a 0.86pp higher year-over-year price change by 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 4 shows the corresponding event study. The vertical axis is scaled so that each coefficient represents the effect of a 1 percentage point increase in the degree of irreversibility on the causal impact of a 1 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.³¹

This relative difference in pricing behavior still appears when I interact the credit supply 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 5 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. As I discussed at the end of Section 2.2, the zero price change can still signify ex-ante higher customer-base

³¹A 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 4: Higher Irreversibility Increases Price Change Response: $\beta_{1,2009:Q3} > 0$



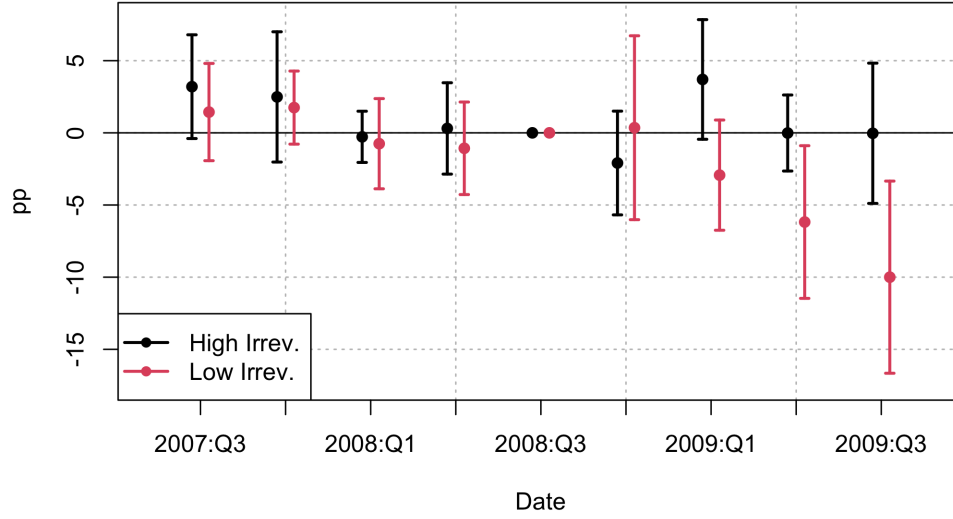
Notes: This figure shows the estimated percentage-point difference in the year-over-year log price change after a 1 standard deviation cut in credit supply when irreversibility increases by 1pp. The coefficients on the credit supply shock's (linear) interaction with irreversibility are instrumented with 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 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.

investment because if firms have inventories, then a firm can simultaneously cut production and inventories. The first effect decreases output sold while the second increases output sold, and it is entirely possible for the two effects to cancel out.

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

Appendix D.1 checks that these results are robust. First, I report the reduced form.

Figure 5: 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 for firms with high versus low irreversibility after a 1 standard deviation 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 $H(\text{Irrev})$. Bars are 95% confidence intervals. 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.

Second, I re-run the regression with additional balance sheet controls from Compustat or QFRCEN. Some firms are dropped because of missing data. Third, I change the irreversibility measure to be the predicted liquidation value of tangible capital as a share of total assets, which generates firm-level variation in how much potential liquidity could be raised after accounting for the irreversibility of PPE. Fourth, I check the sign and significance of the interaction coefficient for a variety of other specifications. Appendix C.3 also checks first stage diagnostics.

While the levels of the price responses in Figure 5 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 what the results should have been is that firms with greater 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 with greater irreversibility 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.

Robustness to Export Prices. A reasonable concern is that these results may be specific to this sample of firms found in the PPI and that I chose to run the regression in growth rates instead of levels. To this end, 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.³² 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.³³ Second, the previous regressions did not saturate the covariates,

³²I 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.

³³[Kim \(2021\)](#) and [Renkin and Züllig \(2024\)](#) both find that demand elasticity helps explain heterogeneity in how prices respond to credit supply shocks.

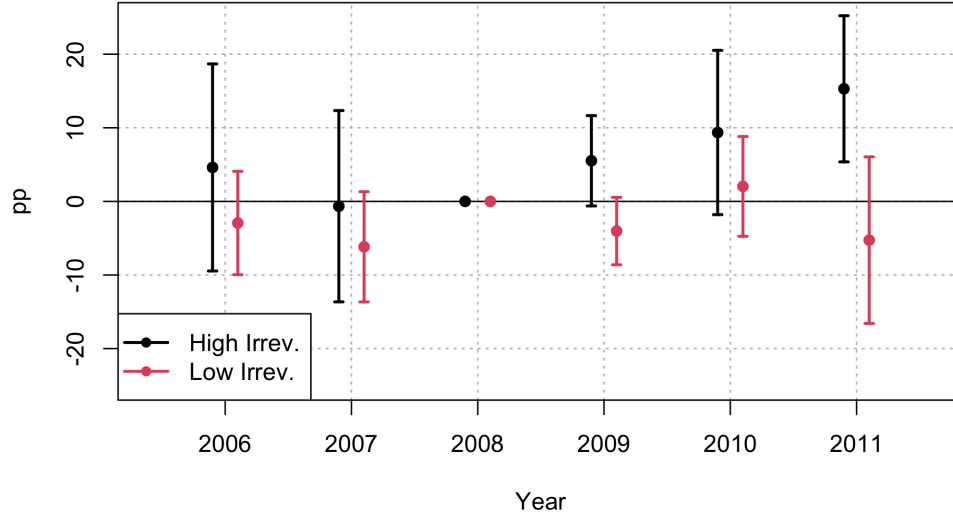
so differences in pre-crisis characteristics across industries with high versus low irreversibility may explain the difference in price responses. I address these concerns by running

$$\begin{aligned} \log p_{g,f,t} = & \sum_{k \in T} \mathbb{1}(t = k) \left[\beta_{0,k} \left(-\Delta \tilde{L}_f \right) + \beta_{1,k} \left(-\Delta \tilde{L}_f \times H(\text{Irrev}_{\text{ind}(f)}) \times H(\text{Elast}_g) \right) \right] \\ & + \sum_{k \in T} \mathbb{1}(t = k) \left[\gamma_{0,k} H(\text{Irrev}_{\text{ind}(f)}) + \gamma_{1,k}^\top X_f + \gamma_{2,k}^\top (X_f \times H(\text{Irrev}_{\text{ind}(f)})) \right] \quad (9) \\ & + \Gamma_{g,t} + \Gamma_{\text{ind}(f),t} + \varepsilon_{g,f,t} \end{aligned}$$

where H will be an indicator for above/below median, and the granularity of the product group g is HS6. By additionally interacting the credit supply shock $\tilde{L}_f$ with the demand elasticity Elast_g , I can compare the response of prices with goods with similar demand elasticities sold by firms in industries with different levels of irreversibility. I measure demand elasticities using estimates from [Soderbery \(2015\)](#), which improves upon estimates from [Broda and Weinstein \(2006\)](#). 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.

Exporters in industries with high irreversibility still choose higher price changes than exporters in industries with low irreversibility, holding constant the product-level demand elasticity. In the main text, I focus on the price response for low demand elasticities shown in Figure 6, while Figure D.5 in the Appendix reports the results for both high and low demand elasticities. Consistent with a stronger customer-market incentive and with evidence from [Renkin and Züllig \(2024\)](#), exporters of goods with low demand elasticities in high-irreversibility industries raise prices after a cut in credit supply. By 2011, the price level relative to 2008 is nearly 15pp higher. It is also notable that the relative difference in coefficients in 2009 lines up is also roughly 10pp apart, like the corresponding regression with PPI data in Figure 5. Note that I construct prices as annual unit values, and since LFTTD records data at a monthly frequency like the PPI, I select the last month of transactions for

Figure 6: Exporters with High Irreversibility Raise Prices for Low Demand Elasticity Goods



Notes: This figure shows the estimated impact of a 1 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. 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 D.5 in Appendix D.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 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.

a given year to line up with 2008:Q3 in the PPI sample. So 2009 in Figure 6 is constructed from transactions over 2008:Q4-2009:Q3.

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. \(2020\)](#) using data from [Blackwood et al. \(2023\)](#)'s Collaborative Micro-Productivity Project (CMP), which is constructed from the Census's ASM/CMF data.

I compute the markup of a manufacturing establishment e owned by firm f in industry s at time t as

$$\mu_{e,f,s,t} = (\alpha_{s,t}^L + \alpha_{s,t}^M) \frac{\text{Sales}_{e,f,s,t}}{\text{Payroll}_{e,s,f,t} + \text{MaterialsCost}_{e,s,f,t}}, \quad (10)$$

where $\alpha_{s,t}^L$ and $\alpha_{s,t}^M$ are the cost shares of labor and materials at the 6-digit NAICS level. I restrict the sample to establishments owned by firms observed in the LFTTD sample. To mirror the granularity of the product groups in the LFTTD regression (9) for Figure 6, I construct the sales-weighted average markup across establishments with the same 4-digit NAICS code owned by the same firm, as 4-digit NAICS is approximately HS6.³⁴ Using this markup, I run a regression similar to the LFTTD price regression (9) but use the log markup on the left-hand side and interpret the 4-digit NAICS codes as product group codes.³⁵

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. I am in the process of disclosing the numerical estimates, but I can report their sign and significance, as shown in Table 3. Over 2009-2011, there is a marginally significant increase in the log markup over 2009 for firms with high irreversibility, and afterward the significance vanishes, consistent with a temporary rise in markups. The difference in markup responses is also statistically significant at the 5%

³⁴When [De Loecker et al. \(2020\)](#) compute firm-level markups using the ASM/CMF data, they define a firm as a group of establishments with the same 4-digit NAICS code and the same Census parent firm identifier.

³⁵I 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 July 2005-2006. 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 3: Markups Rise in High-Irreversibility Industries

	2008	2009	2010	2011
High Irreversibility	+	+	+	+
Low Irreversibility	+	—	—	—
Sig. Diff. ($p < 0.05$)	N	Y	N	N

Notes: This table reports the sign and significance of the credit supply shock coefficient by above/below median irreversibility. The dependent variable of the regression is the log sales-weighted markup across establishments with the same 4-digit NAICS code owned by the same firm. 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 $H(\text{Irrev})$. Standard errors are clustered by primary lender. The bottom row of this table reports the significance at the 5% level of the interaction coefficient. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.

4.3 Alternative Explanations

In this section, I consider alternative explanations for my results and argue why they may be less plausible than my preferred explanation.

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.³⁶ If unmodeled menu costs penalize 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 B.5b in Appendix B.3, presumably because firms lease capital to serve as a hedge against the costs of irreversibility (see Fairhurst et al. 2026, Chowdhury et al. 2025) or low borrowing capacity (see Eisfeldt and Rampini 2009, Kermani and Ma 2023). Assuming leased capital is easier to adjust in the short run, the mechanism in Altig et al. (2011) should actually tilt firms in industries with greater irreversibility to choose *lower* prices changes 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, my mechanism has a cost to capital sales, and it is precisely this cost that motivates insurance through the customer base.

Why Not A Difference in Inventories? The difference in price responses in the PPI sample could be explained by industries with high irreversibility accumulating fewer inventories on average. However, I do not find that irreversibility at the industry level is negatively associated with the average inventory to sale or asset ratios in Figures B.1 and Figures B.2 in

³⁶The 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.

Appendix B.2. In contrast, the descriptive evidence in Section 3.2 suggests a much stronger connection between irreversibility and the customer-market incentive.

Are Firms With Greater Irreversibility Insulated from Liquidity Shocks? Another interpretation of Figure 5 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 could be 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, if this claim is true, then we should expect that firms in industries with high irreversibility would not need to cut their input choices.

However, this explanation is inconsistent with the evidence from export prices and additional evidence on employment growth rates for the PPI sample. Figure 6 shows a significantly positive response for export prices of goods with low demand elasticities 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, I find that firms in industries with high irreversibility cut employment growth more than firms in industries with low irreversibility. I compute the firm-level annual growth rate in employment in March using LBD data.³⁷ Table 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

³⁷I 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.

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 9% over Mar. 2009-2010 after a cut in credit supply.³⁸

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

Year	2009	2010
	(1)	(2)
CSS $\times$ Irrev _{ind(f)}	0.060 (0.289)	-0.613** (0.291)
Predicted Emp. Growth, 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 employment growth when irreversibility is at the 90th percentile. Column (1) is Mar. 2008-2009 and (2) is Mar. 2009-2010. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5 Quantification

This section provides a back-of-the-envelope calculation to illustrate that the estimated differences in the price response to credit supply shocks between high- and low-irreversibility industries is quantitatively meaningful. 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 all industries had

³⁸No 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.

low irreversibility. This exercise abstracts from general equilibrium effects.

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 between irreversibility and credit supply (i.e. the specification for Figure 4), 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 public 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.³⁹ 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 shocks from firms in Dealscan for which I can compute credit supply shocks, not just firms in the PPI or LFTTD samples.⁴⁰ Finally, I aggregate the goods-level counterfactual price changes using the PPI’s importance weights on each goods index.⁴¹

³⁹I use public goods-level price indices because I computed this back-of-the-envelope after my access to the microdata was indefinitely suspended. I use price changes over July 2008-2009 because 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.

⁴⁰This sample is the same as the one I use in Appendix D.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.

⁴¹I have checked that an aggregation of the goods-level price indices using weights from the BLS nearly replicates the official PPIACO series in FRED.

In counterfactual C2, I perform the same procedure but instead of using an industry’s irreversibility estimate, I assume all industries have the same level of irreversibility as 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, holding constant the counterfactual change in credit supply. Technically, it is a change in each industry’s characteristics correlated with irreversibility to the characteristics of the least irreversible industry.⁴² 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 percent change in the PPI index over July 2008-2009 is about 19%.⁴³ 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 were 39.1% more rigid because there are differences in irreversibility (and correlated characteristics) across industries.

6 Conclusion

This paper shows that investment irreversibility makes output prices more rigid because irreversibility strengthens the customer-market incentive. I find empirical evidence in support of this hypothesis. A back-of-the-envelope calculation suggests that aggregate prices would have been almost 40% more rigid after reductions in credit supply than if all industries

⁴²This industry is primary metals in the public PPI data.

⁴³This PPI index is the aggregation of the goods-level indices using 2008 importance weights. The large magnitude of the actual price change does not necessarily go against the missing deflation puzzle (e.g. [Hall 2011](#), [Ball and Mazumder 2011](#)) because the missing deflation puzzle is about consumer price inflation, not producer price inflation.

Table 5: 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 due to Irreversibility			39.1

Notes: C1 relaxes firm-specific credit supply shocks tighter than the 10th percentile to the 10th percentile, holding each industry’s actual level of irreversibility fixed. C2 applies the same credit-easing as C1, but additionally sets every industry’s irreversibility to the level of the least irreversible industry in the sample (primary metals). The Actual column reports the percent change in aggregate PPI index computed by aggregating goods-level price indices using the 2008 importance weights over July 2008-2009. The other two columns 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.

had the same characteristics—and in particular the same level of irreversibility—as the least irreversible industry.

I leave several avenues for future research. In ongoing work in [Chen \(2026\)](#), I develop a heterogeneous-firm model with partially irreversible investment, customer markets, and endogenous demand uncertainty. This model will show that differences in irreversibility can generate quantitatively significant differences in the customer-market channel that can match my estimates of the difference in price responses to credit supply shocks between industries with high and low irreversibility. With such a model, I can study counterfactual scenarios that explicitly incorporate the interaction between irreversibility and demand uncertainty. While my analysis focused on investment irreversibility, other types of input adjustment frictions likely shape a firm’s incentive to acquire a sticky customer base as a way to deal with demand uncertainty. For example, human capital is a significant and partially irreversible investment by firms because workers acquire human capital over time and are imperfectly substitutable. If some firms find it harder to replace their workers, then they may invest

more in sticky customer bases to ensure that they do not need to frequently adjust their employment. Indeed, [Meeuwis et al. \(2025\)](#) argues that firms respond to adverse risk premia shocks by firing low-skill and/or young workers because the returns from these workers are backloaded into the future since these workers need time to accumulate human capital. [Jäger et al. \(2024\)](#) also estimates that workers are very costly to replace due to imperfect substitutability.

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Appendices

A Data

This appendix section describes the construction and cleaning of all datasets used in the empirical analysis.

A.1 Cleaning by Dataset

Definition of a Parent Firm. In several of the datasets I use, there is a distinction between an establishment and the parent firm. An establishment refers to a place of business at a single physical location. Many firms operate multiple establishments. In the LBD, establishments owned by the same parent firm are linked within a year using the identifier `firmid`. When a firm is privately owned, I use `firmid` as the parent identifier. When a firm can be linked to Compustat using the Census Bureau’s internal bridge with the LBD, I use `gvkey` as the parent identifier. This choice matters because a single `gvkey` can be linked to multiple `firmids`.

PPI. The initial cleaning of the PPI uses [Gilchrist et al. \(2017\)](#)’s script from the replication kit, with the addition of some fields like the buyer type. The cleaning steps are as follows. I remove matrix-weighted and imputed prices. The microdata assigns each item a unique code, where an item includes many price-determining characteristics, including type of buyer, color, and size. I retain an item if it has at least three non-missing price observations, and if reported shipment values are strictly positive. Shipment values are deflated to millions of dollars. I aggregate buyer types into one of three categories (“Final User”, “Intermediate”, and “Same Price to All”) from a much larger number of codes. I exclude exports and sales to government entities.

The BLS records both a transaction price and a base price for each item; the base price is updated to reflect changes in product quality or specifications. The quality-adjusted price is computed as the ratio of the transaction price to the base price, and all price-change regressions use this quality-adjusted measure. Specifically, if $\tilde{p}_{i,t}$ denotes the transaction price on item i at time t and $p_{i,t}^b$ denotes the base price, then the quality-adjusted price is

$$p_{i,t} \equiv \frac{\tilde{p}_{i,t}}{p_{i,t}^b}. \quad (\text{A.1})$$

Relative shipment weights in the microdata are reported at the establishment level rather than at the firm-parent level. Formally, the firm-level weight on good i for establishment e in firm f at time t is

$$w_{i,e,f,t} = w_{i,e,f,t}^* \frac{\sum_i w_{i,e,f,t}^*}{\sum_e \sum_i w_{i,e,f,t}^*}, \quad (\text{A.2})$$

where $w_{i,e,f,t}^*$ denotes the relative weight of good i in the production structure of firm f at establishment e as recorded by the BLS, and the second term adjusts for the fact that PPI weights on goods are defined by establishment rather than parent firm.

Monthly log price changes are winsorized at $\pm 100\%$ at the item level before aggregation. I compute quarterly log price changes from the monthly series. Four-quarter log price changes are computed as the sum of quarterly log changes over a rolling window. I retain product groups with at least five distinct firms so that the product group fixed effects are not too noisily estimated.

LBD. The LBD provides establishment-level employment, industry classification, and geographic identifiers for 2004–2011. I harmonize NAICS to 2002 using the vintage-consistent version from [Fort and Klimek \(2016\)](#). I assign a firm a 3-digit NAICS code using the employment-weighted mode across its establishments, excluding management establishments

with 3-digit NAICS code 551.

I use the LBD to create longitudinal panels. The LBD’s longitudinal identifier for parent firms, `lbdfid`, works reasonably well but has several deficiencies.⁴⁴ I augment this identifier in two ways. First, I use `gvkey` as a longitudinal identifier when possible. Second, if the current year’s `lbdfid/gvkey` does not exist in the following year, then I identify the headquarters establishment in the current year and use its `lbdfid/gvkey` in the next year as the successor firm-level identifier. The headquarters is defined as the largest management establishment by employees if one exists and otherwise the largest establishment across any industry code by employees. Ties are broken by payroll. A longitudinal panel created in this manner will vary with the year in which the panel is initialized. I construct two linkages using 2004 and 2005 as starting cohorts.

I also use the LBD to measure firm employment size and age for covariates. Firm employment in March 2007 is aggregated from the LBD to the firm level using the firm parent identifier. When I construct the PPI-Census-Dealscan dataset, I drop any firms with fewer than 10 employees. Firm birth year is determined by the earliest of three sources: the year the LBD first records positive employment, the year the LBD first records positive payroll, or the Compustat–CRSP link date for public firms (based on the `permco`). Firm age is then 2007 minus the birth year plus one.

Finally, I measure employment growth over time using the LBD. First, over 2006–2010, I compute the [Davis et al. \(1996\)](#) (DHS) growth rate at the establishment level. Second, for each year from 2006 to 2010, firm-level employment and DHS employment growth are constructed by aggregating LBD establishment-level data to the firm level. See [Chodorow-Reich \(2014\)](#) for details on how the establishment-level growth rates can be used to create the firm-level growth rates.

⁴⁴See [Chow et al. \(2021\)](#) for more details.

Dealscan. The loan sample is constructed following [Chodorow-Reich \(2014\)](#). Dealscan loan facilities are restricted to borrowers that satisfy all of the following criteria: (i) US-domiciled, (ii) not in the finance, insurance, or real estate sectors (SIC codes 60–69), (iii) primary loan purpose is either “Corporate purposes” or “Working capital”, and (iv) either the facility start date falls between January 2004 and August 2008, or the facility ends after October 2007. When constructing the credit supply shocks, I consolidate banks to their parent bank.⁴⁵ I impute lender shares using the predicted values from regression estimates provided by [Blickle et al. \(2022\)](#) when available and otherwise the average lender share for a lead/participant in syndicates with the same structure. Finally, multiple borrowers can be linked to the same parent firm in the Census Bureau. For example, Dealscan may identify subsidiaries as separate borrowers. I construct the credit supply shock, instruments, and controls initially at the Dealscan borrower level and then aggregate to the parent firm level using the size of the last loans for each Dealscan borrower as weights. For categorical controls, I aggregate using the economically meaningful choice. For example, the indicator for a credit line equals one if any of the last loans was a credit line.

FISD. I exclude firms in the finance, insurance, and real estate industries and retain bonds with offering dates before September 1, 2008. I classify a firm’s access to bond markets into three categories. Firms which have no matched FISD issuer id are grouped together as having zero bond issuance. Firms which have issued at least one investment grade bond in their history are classified as “investment grade”. All other firms are grouped together into a third category.

Compustat. I construct balance sheet controls from Compustat within each quarter and then average over 2006:Q4-2007:Q2. Variables constructed include book leverage, cash-to-assets ratio, average interest rate (interest payments divided by total debt), and the

⁴⁵I thank Gabriel Chodorow-Reich for generously providing me a file with the consolidations he used.

inventory-to-sales ratio. Total debt equals short-term plus long-term debt. Book leverage is total debt divided by the sum of total debt and common/ordinary equity. These controls are used in a robustness check of the main diff-in-diff.

QFRCEN. The 2007 QFRCEN is used to provide balance sheet information for firms not observed in Compustat. QFRCEN firms are mapped to the LBD by EIN. When there are duplicate matches by EIN to a parent firm in a given year-quarter, I identify the best matches using fuzzy name matching and then manually review the suggested candidates.

A.2 Firm Matching Algorithm

I match firms from Dealscan, FISD, and the PPI to Census Bureau records using their name, address, and industry information. To perform matching, I use tools from the `fedmatch` package created by [Cohen et al. \(2021\)](#). Before matching, all firm names are standardized: text is lowercase, special characters (brackets, slashes, hyphens) are replaced with their word equivalents, punctuation is removed, standard abbreviations are expanded to long-form words (e.g. “corp” to “corporation”, “mfg” to “manufacturing”), and whitespace is stripped. This step creates the “long” version of the name. I also create a “short” version of the name in which I remove common words in firm names like “company” and “incorporated”.

I create candidate matches in multiple stages. In each stage, the candidate match is proposed based on a name and exact state match.

1. Exact name match of the long name
2. Match of the long name based on weighted Jaccard distance. This distance penalizes differences involving rare words more heavily than differences involving common words, like “corporation”. See [Cohen et al. \(2021\)](#) for more details.
3. Fuzzy matching using the Jaro–Winkler distance

4. Repeat 1-3 using the short name.

Exact name matches from stages 1 and 4 as well as matches from stage 2 which would become exact name matches after dropping common words are automatically accepted if there exists an establishment under the same firmid in the LBD with an exact city/zipcode match or matching industry information. All other candidate matches are manually reviewed.

My matching strategy also accounts for differences in how the datasets handle names. The PPI records historical names, so I can just match PPI respondents which have data in the year 2007 to the 2007 CBPBR. I choose this specific year as the anchor year for the PPI-CBPBR bridge because the Census Bureau’s company organization data is most accurate in an Economic Census year, and this year occurs right before the Lehman bankruptcy. Public firms in Dealscan and FISD can be indirectly linked via Compustat. [Chava and Roberts \(2008\)](#) created and updates a link from Dealscan firms to Compustat, which allows me to use the Census Bureau’s Compustat-SSEL bridge for these firms. A subset of FISD can be linked to Compustat using historical issuer CUSIPs in the Compustat-CRSP linking file. Other firms in Dealscan and FISD are linked by name. Note that Dealscan and FISD are “header” datasets, so their company data reflects current information rather than historical information. To deal with this issue, I match firms to the 2020 CBPBR first and then check if there are matches in 2007 at the establishment level by lbdnum, which is an accurate longitudinal identifier according to [Chow et al. \(2021\)](#). This approach deals with the possibility that a firm changed names or headquarter locations between 2007 and the present. Firms in Dealscan or FISD with no matches at this point are then matched directly to the 2007 CBPBR. For example, firms that shut down before 2020 will not appear in the 2020 database. Finally, to maximize coverage, I also link unmatched PPI respondents directly to Dealscan and use the Dealscan-CBPBR link to assign a firmid to more PPI respondents, since the address information in Dealscan is higher quality than the PPI’s.

B Additional Descriptive Evidence on Investment Irreversibility and Customer Markets

B.1 Robustness of Relationship Between Investment Irreversibility and Selling Expenses

This section shows that the estimated relationship between investment irreversibility and selling expenses is a robust feature of the data. In each of the tables below, I show that the relationship and R^2 values are robust to (i) restricting the sample period to a short pre-Lehman period 2004-2007 and (ii) using the ratio of industry-total selling expenses to industry-total sales instead of a firm-weighted average. Table B.1 uses the main text's definition of selling expenses. Table B.2 uses Peters and Taylor (2017)'s measure of selling expenses, which only strips out R&D costs, and Table B.3 just uses SG&A expenses directly as the measure of customer acquisition, as in Gourio and Rudanko (2014).

Table B.1: Selling Expenses versus Investment Irreversibility

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Irreversibility	7.99*** (1.83)	1.83*** (0.32)	1.06*** (0.33)	1.28** (0.49)	0.64*** (0.19)	0.33** (0.13)
Sample	Mfg	Mfg	Mfg	All	All	All
Aggregation	Avg	Median	Sum	Avg	Median	Sum
<i>Fit statistics</i>						
R^2	0.76	0.74	0.39	0.09	0.32	0.17
Observations	17	17	17	48	48	48

Notes: Columns (1)-(3) use the manufacturing-only sample while Columns (4)-(6) use all industries with an available estimate of irreversibility. The second column within each group replaces the sample period from 1997-2019 to the short pre-Lehman period of 2004-2007. The third column within each group uses the ratio of industry-total selling expenses to industry-total sales instead of a firm-weighted average. Robust standard errors are reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Peters and Taylor (2017) Selling Expenses versus Investment Irreversibility

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Irreversibility	8.19*** (1.82)	1.95*** (0.36)	1.13** (0.39)	1.34** (0.50)	0.70*** (0.21)	0.34** (0.14)
Sample	Mfg	Mfg	Mfg	All	All	All
Aggregation	Avg	Median	Sum	Avg	Median	Sum
<i>Fit statistics</i>						
R ²	0.77	0.73	0.38	0.09	0.33	0.15
Observations	17	17	17	48	48	48

Notes: Columns (1)-(3) use the manufacturing-only sample while Columns (4)-(6) use all industries with an available estimate of irreversibility. The second column within each group replaces the sample period from 1997-2019 to the short pre-Lehman period of 2004-2007. The third column within each group uses the ratio of industry-total selling expenses to industry-total sales instead of a firm-weighted average. Robust standard errors are reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: XSGA versus Investment Irreversibility

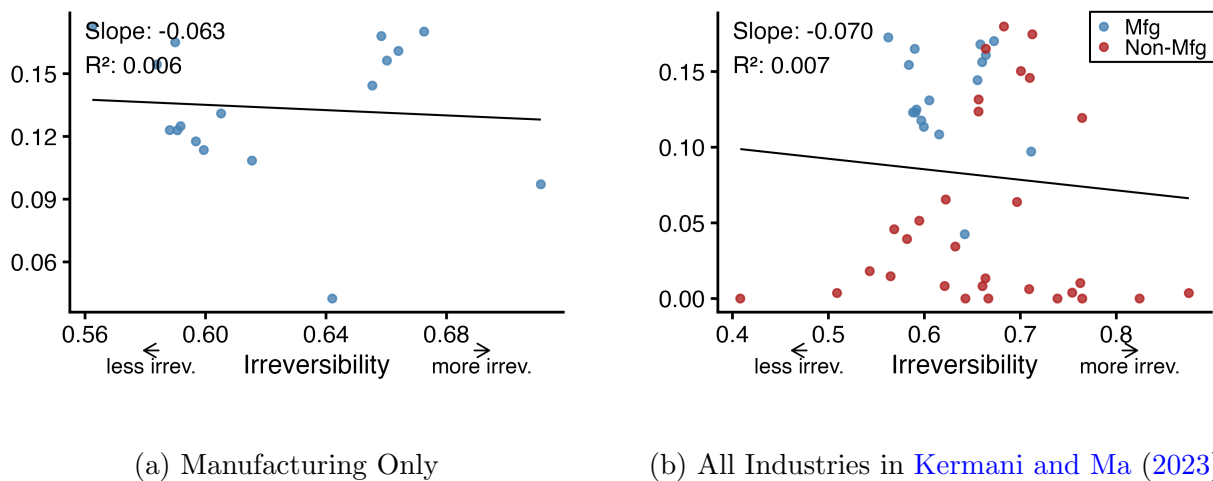
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Irreversibility	12.04*** (3.26)	2.77*** (0.34)	1.64*** (0.29)	1.73** (0.66)	0.82*** (0.26)	0.40** (0.17)
Sample	Mfg	Mfg	Mfg	All	All	All
Aggregation	Avg	Median	Sum	Avg	Median	Sum
<i>Fit statistics</i>						
R ²	0.74	0.86	0.69	0.09	0.28	0.16
Observations	17	17	17	48	48	48

Notes: Columns (1)-(3) use the manufacturing-only sample while Columns (4)-(6) use all industries with an available estimate of irreversibility. The second column within each group replaces the sample period from 1997-2019 to the short pre-Lehman period of 2004-2007. The third column within each group uses the ratio of industry-total selling expenses to industry-total sales instead of a firm-weighted average. Robust standard errors are reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Investment Irreversibility and Inventory Accumulation

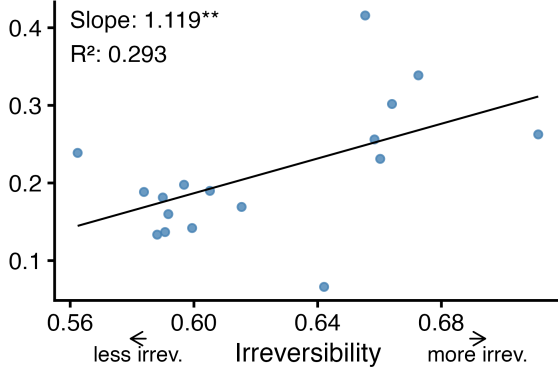
Figures B.1 and B.2 show that industry inventory accumulation does not appear tightly correlated with investment irreversibility. The only case with a significant relationship and a meaningful R^2 is the mean inventory/sales ratio among manufacturers. In that case, however, industries with more irreversible investment accumulate more inventories, which should generally imply a greater ability to cut inventories as a way to raise cash. 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. Indeed, in the PPI-Census-Dealscan dataset, I find a null association between investment irreversibility and inventories as a share of sales and a significantly positive association between irreversibility and inventories as a share of *assets*.

Figure B.1: Median Inventories/Sales

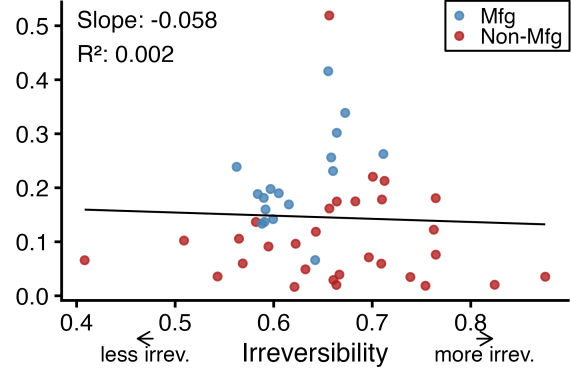


One of the remaining ways in which inventories could explain the causal evidence in Section 4 is that inventories in irreversible industries are harder to liquidate, despite having as many inventories as industries with lower irreversibility. For example, their inventories may require significant effort to find buyers in a short time frame. The type of inventories may also be dominated by work-in-progress inventories, which are not sellable until they are

Figure B.2: Mean Inventories/Sales



(a) Manufacturing Only



(b) All Industries in [Kermani and Ma \(2023\)](#)

fully transformed into the final good.

B.3 Correlations of Investment Irreversibility with Other Industry Characteristics

Figure [B.3](#) illustrates how irreversibility is distributed across industries at the 2-digit SIC code. Note that there is variation in irreversibility among the manufacturing sectors (20-39), and these industries are not the most irreversible. Further, durables manufacturers actually have slightly lower irreversibility on average.

Table [B.4](#) restricts to manufacturing industries and groups them by quartiles of irreversibility. Within each quartile, the industries are listed in ascending order of irreversibility, so the top row of Quartile 1 (primary metal) is the manufacturing industry with the lowest irreversibility and the bottom row of Quartile 4 (chemical products) is the single most irreversible industry.

In this appendix section, I also investigate other industry characteristics that correlate with irreversibility and discuss why these other characteristics are either supportive of my interpretation or unlikely to be the explanation behind the results from the price difference-

Figure B.3: Distribution of irreversibility by 2-digit SIC code.

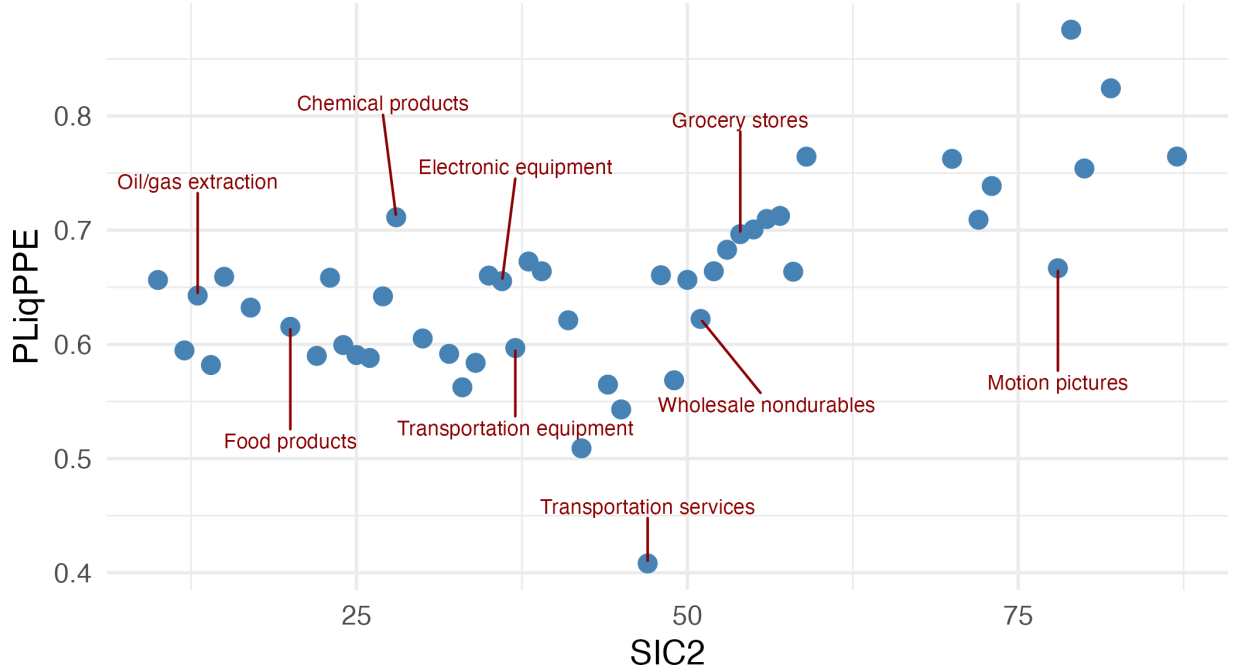


Table B.4: Mfg. Industries by Irreversibility Quartile

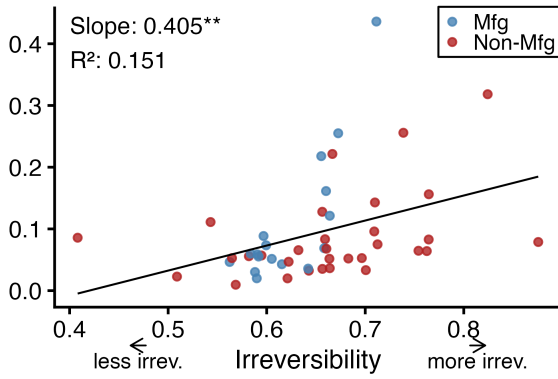
Quartile 1 (lowest irrev.)	Quartile 2	Quartile 3	Quartile 4 (highest irrev.)
Primary metal	Stone, clay, glass, and concrete	Food products	Machinery
Fabricated metal	Transportation equipment	Printing and publishing	Misc. manufacturing
Paper products	Wood products	Electronic equipment	Analytical instruments
Textile products	Rubber and plastics products	Apparel products	Chemical products
Furniture and fixtures			

in-differences in Section 4. At the 5% significance level, higher irreversibility is associated with higher cash/assets, lower book leverage, lower absolute demand elasticities (higher market power), a higher operating lease share, a lower frequency of price adjustment, and a higher perceived discount rate.⁴⁶ I discuss most of these characteristics and their association with irreversibility in the main text. However, I do not discuss demand elasticities and

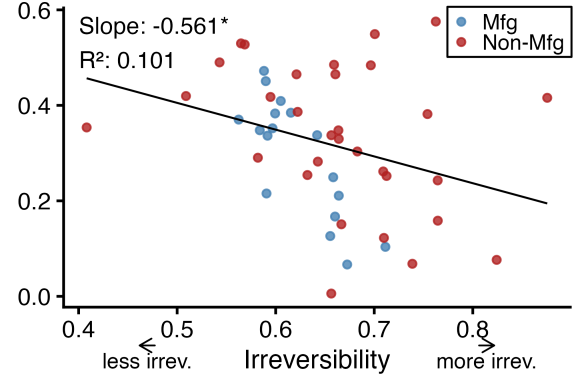
⁴⁶The industry characteristics are measured using Compustat data over the years 1997-2019, with the exception of the operating lease capital share, for which I use data over 2019-2025, and capital intensity, which is measured using BLS industry data. For any firm-year-level characteristic, I aggregate by taking the median within an industry. Demand elasticity is measured at the firm level using Pellegrino (2025)'s estimates. 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).

discount rates. The association of irreversibility with lower steady-state demand elasticity (higher market power) is consistent with the idea that a larger customer base leads to lower intratemporal demand elasticities and could be obtained with the additive form of deep habits in [Ravn et al. \(2006\)](#) and [Binsbergen \(2016\)](#) instead of the relative deep habits specification used in the main text. The association with discount rates is consistent with the idea that irreversibility increases the hurdle rate for investments.

Figure B.4: Cash / Assets and Book Leverage

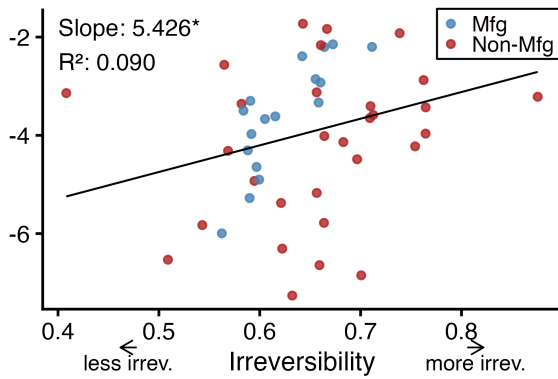


(a) Cash / Assets

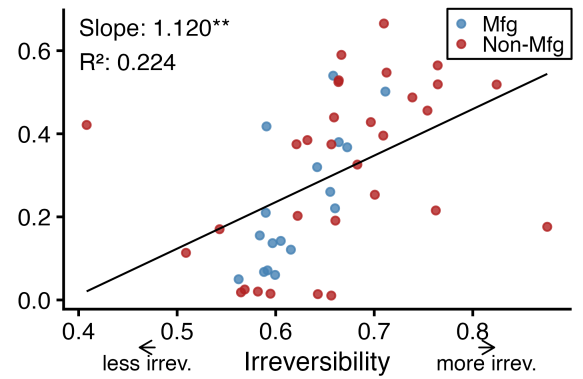


(b) Book Leverage

Figure B.5: Demand Elasticity and Operating Lease Capital Share

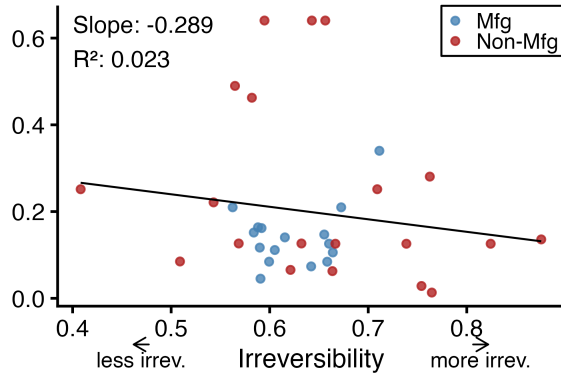


(a) Estimated demand elasticity (DRS)

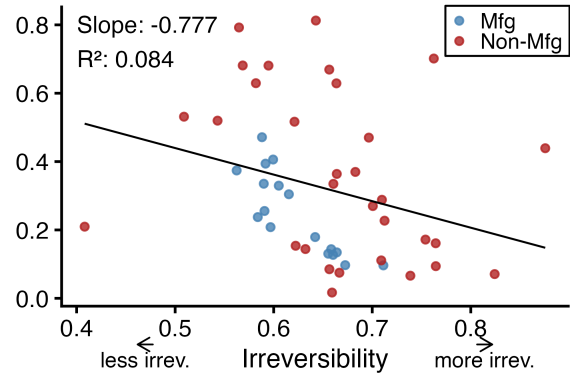


(b) Operating Lease Capital Share

Figure B.6: Capital Intensity and PPENT / Assets

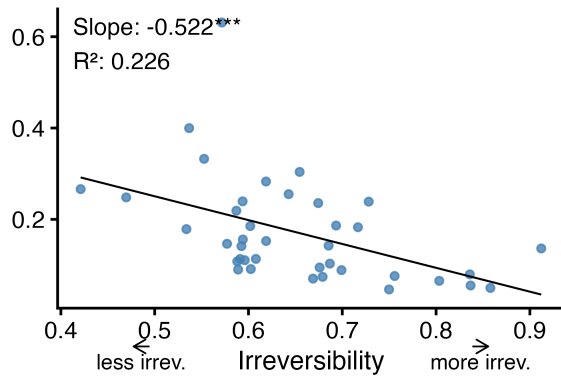


(a) Capital Intensity

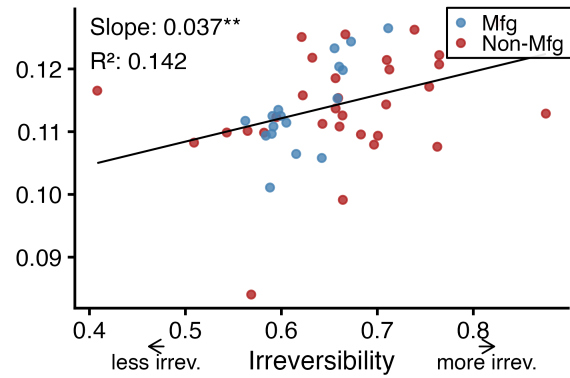


(b) PPENT / Assets

Figure B.7: Frequency of Price Adjustment and Perceived Discount Rates



(a) Freq. of Price Adjustment



(b) Perceived Discount Rate

C Diagnostic Checks for Empirical Analysis

C.1 Khwaja and Mian (2008) Test

This appendix reports the Khwaja and Mian (2008) test discussed in Section 3.4. In short, this test considers firms which signed a new loan over 2008:Q4-2009:Q3 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 C.1 shows, the point estimates are quite close to each other. The differences have similar magnitudes to what Chodorow-Reich (2014) and Kim (2021) find.

C.2 Balance of the Lehman Instrument

Table C.2 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

Table C.1: Estimates of the coefficient on $\Delta L_{f,b}$. 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. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
$-\Delta L_{f,b}$	-2.49^{***} (0.40)	-2.43^{***} (0.43)	-0.33^{***} (0.05)	-0.30^{***} (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

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 D.1, the results still hold.

C.3 First-Stage Diagnostics

Table C.3 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%. I also report the F-statistics from the [Sanderson and Windmeijer \(2016\)](#) test for the baseline regression (8), in which I interact the credit supply shock with irreversibility. Note that this latter test is not a direct test for weak instruments per se, and it assumes homoskedastic errors. Finally, 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

Table C.2: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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 $-\Delta\tilde{L}_f$, i.e. tighter credit supply.

Table C.3: First-stage diagnostics for the Lehman co-syndication IV. The first two rows are from [Olea and Pflueger \(2013\)](#)’s robust test for weak IVs while the last two rows are from [Sanderson and Windmeijer \(2016\)](#)’s test for the coefficient on $-\Delta\tilde{L}_f$ (No-Int. Coef) and $-\Delta\tilde{L}_f \times \text{Irrev}_{\text{ind}(f)}$ (Int. Coef). 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.

Statistic	Estimate
Eff. F-Stat	69.4
Crit. Val. for 10%	23.1
SW (2016) F-Stat No-Int. Coef	141.0
SW (2016) F-Stat Int. Coef	109.0

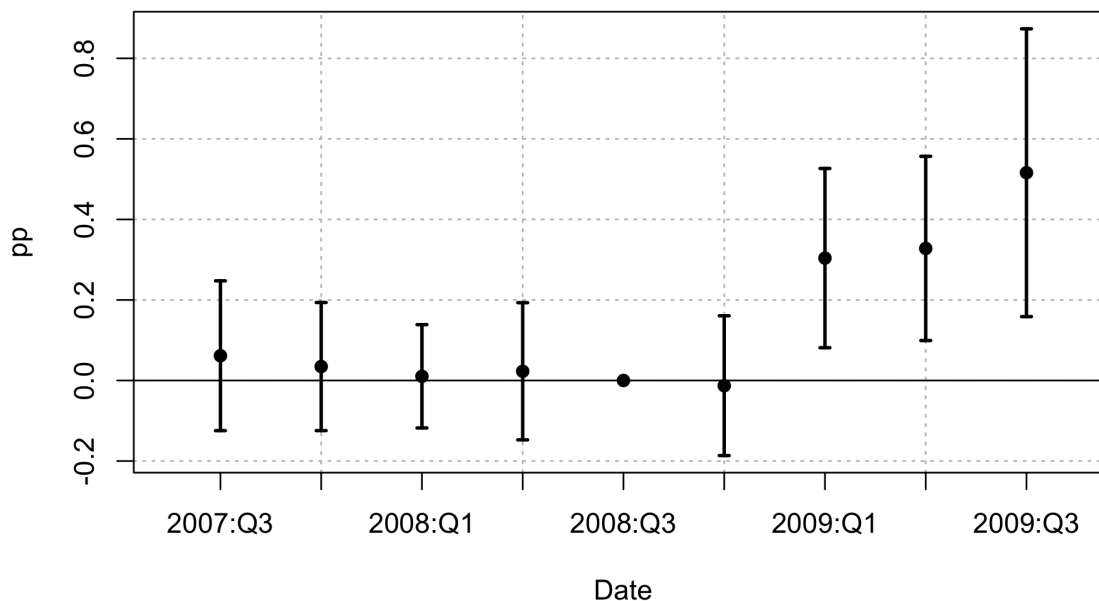
D Additional Results Using Credit Supply Shocks

D.1 Robustness Checks for Price Regressions

Results Using Lehman Co-Syndication IV. Figure D.1 shows the reduced-form estimate of $\beta_{1,t}$ when using the Lehman co-syndication IV. Figure D.2 shows the estimate of $\beta_{1,t}$ when book leverage, average interest rate, cash-to-assets ratio, and inventory-to-sales ratio are added as additional covariates. Figure D.3 shows the estimate of $\beta_{1,t}$ when I interact the credit supply shock with the predicted industry-level recovery rate times the value of PPENT divided by total assets measured in 2007. In other words, this alternative measure of irreversibility is the predicted recovery value of PPE on a firm's balance sheet.

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% 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 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.

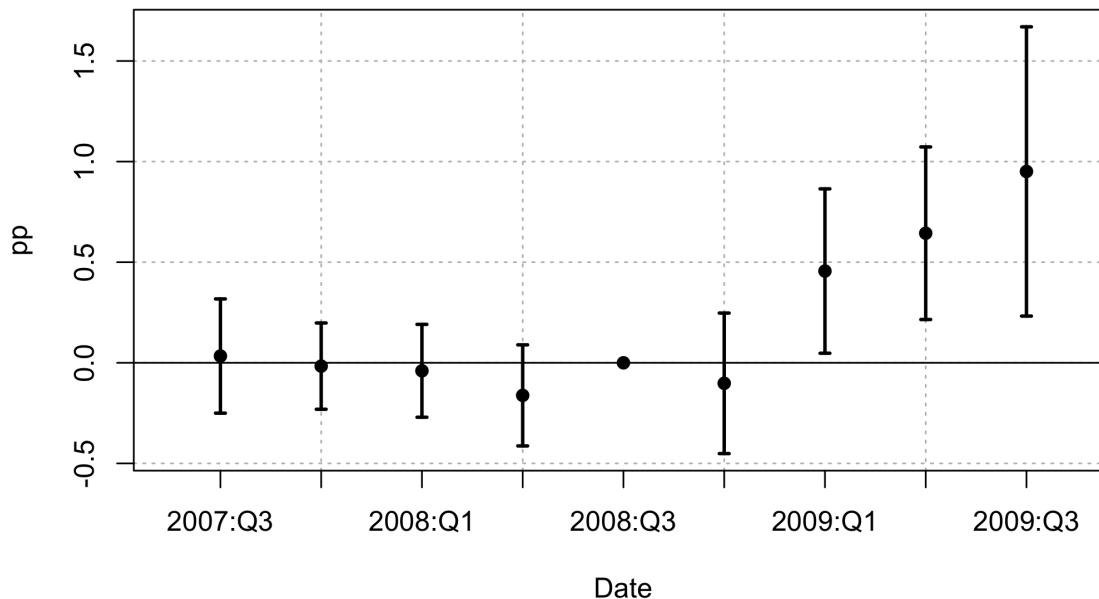
Figure D.1: Reduced Form of Baseline Reg. in Main Text



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.

Potential Pre-Trend in the Levels of the Price Response. One reasonable concern about the estimates in Figure 5, which interacts the credit supply shock with an indicator for above or below median irreversibility, is that there may be evidence of pretrends. Specifically, the coefficient in 2007:Q3 for the above-median group appears quite close to being statistically significant at the 5% level. I argue that this issue is not too big of a concern for two reasons. First, the key novel contribution of my paper is the relative difference in pricing behavior between the two groups. For a triple difference-in-differences, even if there are pretrends, as long as the pretrends are similar across the groups of the third difference (i.e. high versus low irreversibility), we can still claim that a decline in credit supply causes

Figure D.2: Adding Balance Sheet Controls to Baseline Reg. in Main Text

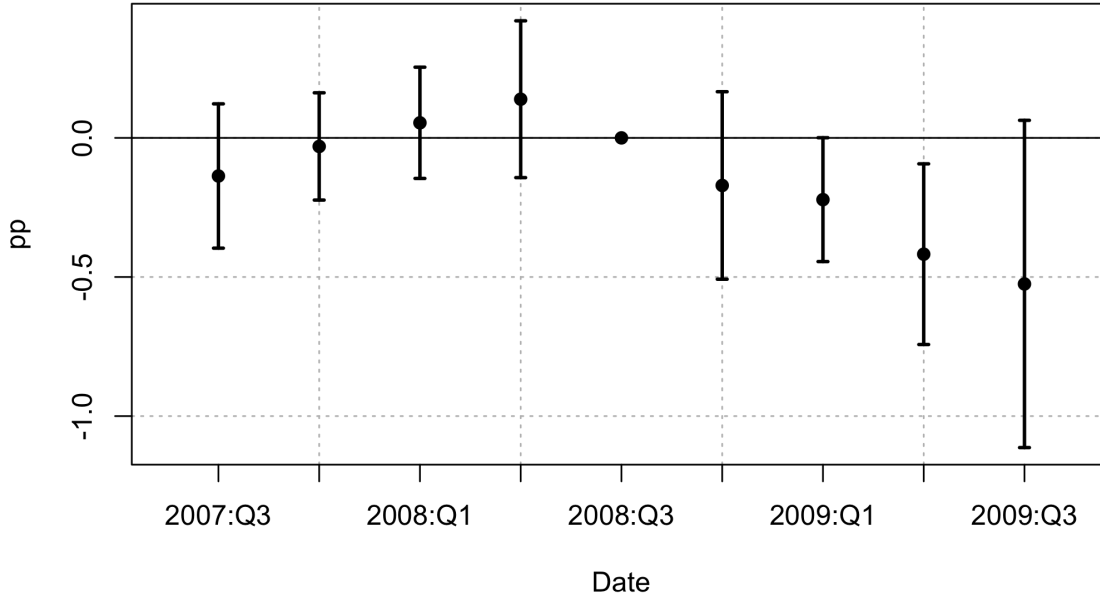


Note: This figure presents estimated effects when I also include as covariates the liquid assets ratio, book leverage, average interest rate on debt, and inventory to sales ratio measured in 2007. Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor 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.

firms in industries with higher investment irreversibility to set higher price changes relative to firms in industries with lower irreversibility.⁴⁷ In my case, the coefficients in Figure 5 are very close to each other in every quarter of the pre-period. Second, in Appendix D.1, I run the reduced-form regression without heterogeneity by irreversibility for the subsample of firms with panel data over 2007:Q1-2010:Q3. With the longer preperiod, this regression does not have evidence of a concerning pretrend, which assuages the concern that exposure to the Lehman co-syndication IV is not independent of shocks or unobserved borrower characteristics that affect price changes. In addition, the shape of the response in the post-period

⁴⁷See Olden and Møen (2022) and Caron (2025)

Figure D.3: Measuring Irrev. with Recovery Value of PPE

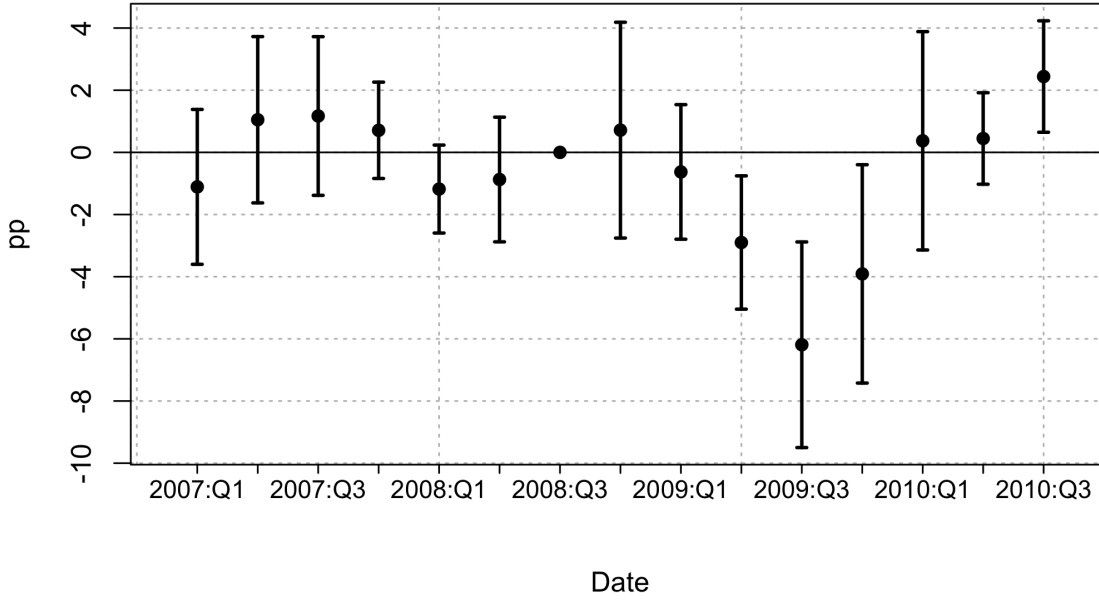


Note: The figure presents estimated effects when I measure irreversibility as the predicted industry-level recovery rate times the value of PPENT divided by total assets measured in 2007. A higher value indicates that a firm get more cash back if it sold its PPE, hence the flip in the sign of $\beta_{1,t}$. 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.

resembles what [Kim \(2021\)](#) finds with data on consumer packaged goods.

Results Using Other Instruments. My results are robust to using two other instruments from [Chodorow-Reich \(2014\)](#), namely exposure to the ABX index and bank deposit-to-assets ratio in 2007. The evidence in Table [D.1](#) is weaker, but the signs are consistent with what I find using the Lehman co-syndication instrument. These regressions also include the balance sheet controls of Figure [D.2](#).

Figure D.4: 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.

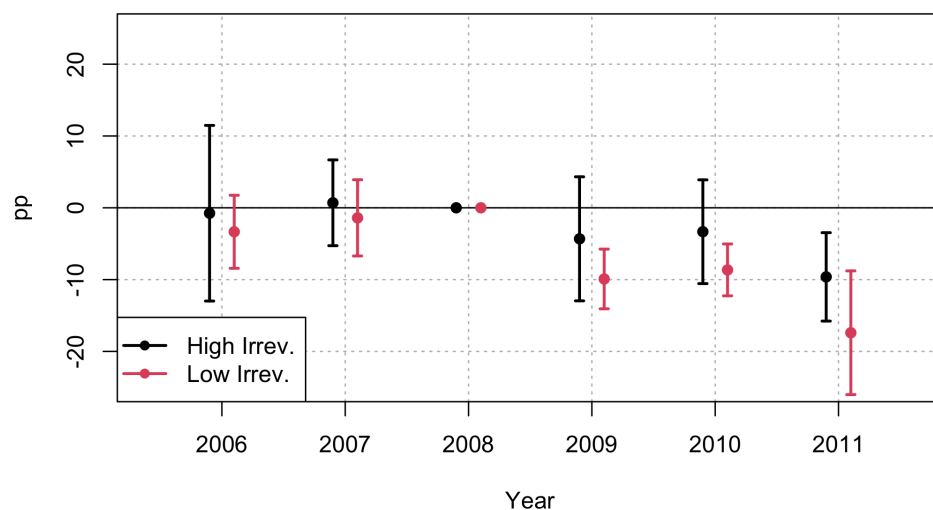
Table D.1: Sign and Significance of When Using ABX and Deposits/Assets Instruments.

Coefficient	ABX	Deposits/Assets
$\beta_{1,2009:Q1}$	+	+*
$\beta_{1,2009:Q2}$	+	+*
$\beta_{1,2009:Q3}$	+*	+

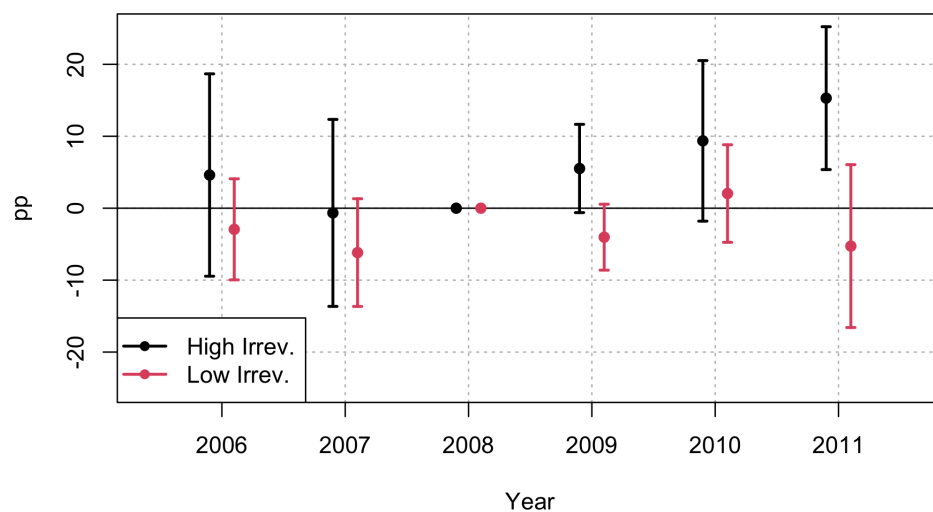
Note: Any views expressed are those of the authors and not those of the U.S. Census Bureau or Bureau of Labor Statistics (BLS). The Census Bureau and BLS have reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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. In Appendix [B.3](#), I also find that, at the industry level, higher irreversibility is mildly correlated with a lower demand elasticity (higher market power). So it is possible that the results are entirely due to differences in demand elasticities rather than differences in irreversibility. Figure [D.5](#) reports the event-study figures for both high and low demand elasticity groups. In either case, there are statistically significant differences in the price between firms in high- versus low-irreversibility industries. The difference in point estimates do appear to be larger though for low demand elasticities.

Figure D.5: 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 elasticity (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.

Consumer Packaged Goods Do Not Drive Pricing Behavior. However, when I compare the impact of a credit supply shock on the price change when a firm sells a consumer packaged good to other product groups, I do not find a statistically significant difference in price changes. Table D.2 defines consumer packaged goods industries with NAICS codes. For both product types, I estimate price cuts after a decline in credit supply.⁴⁸ This finding partially assuages the concern that the difference in pricing behavior after a credit supply shock may result from demand elasticities rather than irreversibility.

Table D.2: Definition of Consumer Packaged Goods Industries Using NAICS Codes

NAICS	Description
311	Food manufacturing
312	Beverage and tobacco product manufacturing
313/314	Textile mills or textile product mills
315	Apparel manufacturing
316	Leather and allied product manufacturing
323	Printing and related support activities
3254/6	Chemical manufacturing for soap, detergents, cleaning and polishing prep., perfumes, toilet prep., and pharmaceutical goods
3399	Sports goods, games, and toys

TFPR as a Proxy for Prices The response of log TFPR growth to the credit supply shock provides additional evidence about the behavior of firms’ prices. TFPR is “revenue” TFP and is distinct from TFP because TFPR measures productivity in terms of revenue rather than physical output, meaning a firm’s TFPR equals physical productivity *times the firm’s price*. An increase in TFPR can reflect either an increase in physical productivity or any shift that raises prices (see Foster et al. 2008). Under the assumption that an adverse credit supply shock does not increase productivity, evidence of positive TFPR growth can be interpreted as an increase in prices.

I measure TFPR using estimates from Blackwood et al. (2023)’s Collaborative Micro-

⁴⁸To limit the number of disclosed estimates, I only report the sign and significance of these regressions.

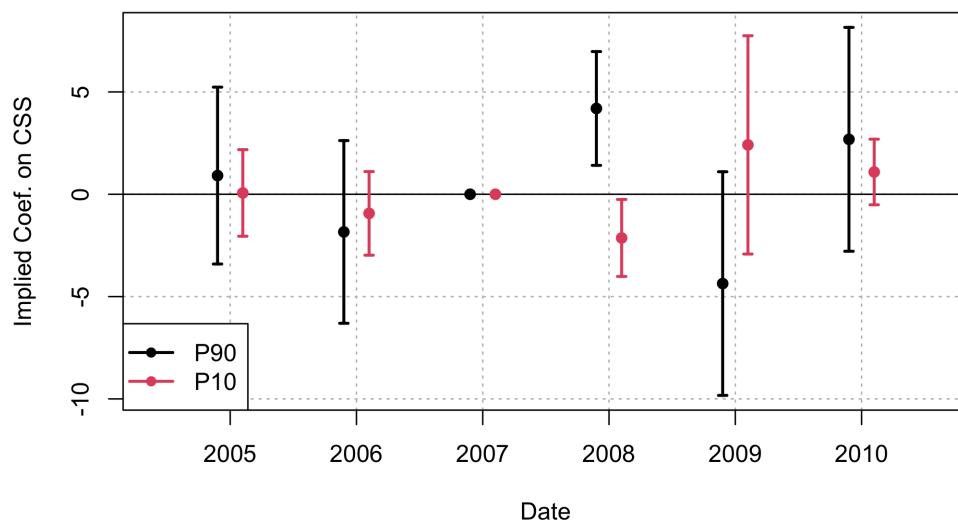
Productivity Project (CMP). The CMP estimates TFPR using a production function accounting approach with the Annual Survey of Manufactures (ASM) and Census of Manufactures (CMF). These estimates deflate revenue with industry deflators, so any price changes should reflect within-industry changes, which bolsters the interpretation of positive TFPR growth as an increase in a firm’s price to generate internal liquidity relative to other firms in the same industry. I compute the sales-weighted average TFPR across establishments with the same 4-digit NAICS code and parent firm. Then I use year-over-year growth in firm by 4-digit NAICS TFPR as the outcome variable in a difference-in-differences regression similar to (8). The product group by time fixed effects are replaced with 4-digit NAICS by time fixed effects since many firms operate establishments in multiple industries at the 4-digit NAICS level.⁴⁹

After a decline in credit supply, firms in industries with high investment irreversibility temporarily increase their prices while firms in industries with low investment irreversibility temporarily cut their prices. Figure D.6 shows this result in an event study by reporting the estimated impact of a credit supply shock on TFPR growth for firms with irreversibility at the 90th percentile of the distribution versus firms with irreversibility at the 10th percentile.⁵⁰ There is a lack of a pre-trend in 2005 and 2006, but firms with high irreversibility have positive TFPR growth in 2008 followed by negative TFPR growth of similar magnitude in 2009. Thus, the level of TFPR rises only temporarily. The opposite occurs for firms with low irreversibility. Note that annual TFPR is based off the entire year’s production, so the data behind the TFPR estimate in 2008 includes 2008:Q4, the quarter after the Lehman bankruptcy. This spike in TFPR growth is consistent with the nearly significant response of

⁴⁹It is not necessarily the case that the 4-digit NAICS codes of a parent firm’s establishments are strict subsets of the parent firm’s 3-digit NAICS code. In the LBD, an establishment’s industry code is determined by its production independent of the parent firm. For example, the 2-digit NAICS code for the headquarter establishment of a multi-unit firm may be 55 because the establishment primarily provides management services, even if the firm is a manufacturer.

⁵⁰Due to the smaller sample size for this regression, I report OLS estimates and do not instrument with the Lehman co-syndication IV.

Figure D.6: High (Low) Irreversibility Firms Temporarily Raise (Cut) TFPR



Notes: This figure shows the predicted impact of a credit supply shock on TFPR growth for firms with irreversibility at the 90th percentile of the distribution versus firms with irreversibility at the 10th percentile. Bars are 95% confidence intervals. 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.

year-over-year price changes in 2009:Q1 in Figure 5, as that would have been the year-over-year price change in January of 2009.

D.2 Credit Market Outcomes and Characteristics

This section checks the impact of credit supply shocks on credit market outcomes following [Chodorow-Reich \(2014\)](#) and extends the analysis to study whether investment irreversibility is associated with differential credit-market responses. [Chodorow-Reich \(2014\)](#) estimates both extensive and intensive margins of credit-market outcomes. On the extensive margin, he estimates the effect of the Dealscan credit supply shock on the probability that a borrower obtains a new loan or a favorable modification of an existing loan over 2008:Q4-2009:Q2. On the intensive margin, he estimates the change in the all-in drawn spread between the last syndicated loan before the Lehman bankruptcy and a newly signed loan over 2008:Q4-2009:Q2. I replicate these regressions and then study heterogeneity by irreversibility for the extensive margin. The sample size for the intensive margin is too small. As in [Chodorow-Reich \(2014\)](#), I run the regressions on all available Dealscan borrowers, not just those in the PPI-Census-Dealscan dataset.

There are four differences in my data and how I run the regression compared to [Chodorow-Reich \(2014\)](#). First, I correct the lender shares that construct the credit supply shock using [Blickle et al. \(2022\)](#)'s code, which accounts for the fact that lead arrangers are likely to sell their stake for certain types of loans. Second, I use Dealscan data downloaded in 2024. Since Dealscan updates its data over time, company characteristics like the primary SIC code may not match what [Chodorow-Reich \(2014\)](#) used. Third, I classify borrowers as public or private based on [Chava and Roberts \(2008\)](#)'s file instead of Dealscan's own classification. Fourth, I do not interact all-in drawn spread with the loan type, and I do not interact the public firm indicator with the bond access indicator for the same reason. The reason is that I run a specification in which I fully saturate covariates with an indicator for above/below median irreversibility. I do not interact public with bond access to avoid splitting small cells.

Results. Tighter credit supply reduces loan supply along both the extensive and intensive margins. Table D.3 reports the results. Columns (1) and (2) are replications of Chodorow-Reich (2014)’s analysis, while Column (3) extends the extensive margin regression by interacting the credit supply shock and all covariates except the state fixed effect with an indicator for whether the borrower’s industry has above- or below-median irreversibility. Columns (1) and (2) show that a one-standard-deviation credit tightening lowers the probability of obtaining a new loan or a favorable modification by about 4 percentage points and raises the all-in-drawn spread by 36 basis points. The third column shows that the extensive margin result applies to firms with high and low irreversibility. Although the probability of a new loan or favorable modifications falls by less for firms with high irreversibility, the difference is not statistically significant at the 5% level. Nonetheless, the small attenuation is consistent with Section B.3, which shows that firms in irreversible industries have more cash on hand and lower leverage, so they may be less sensitive to credit supply shocks.

The small size of the intensive margin effects makes the working-capital channel seem like an unlikely explanation for the large difference in pricing behaviors that I estimate. If the intensive margin effects of the credit supply shock for across high and low irreversibility industries resemble the extensive margin effects, then we should expect a similar or a smaller increase in the cost of working capital for firms in industries with high irreversibility. Also, even if all variable inputs in a period required working capital loans to finance, we would need a difference in the intensive margin effect by almost 10pp. Since a 1 standard deviation credit supply shock only increases the interest rate on a new loan by less than 1pp and since working capital does not seem to explain the effect of tighter financial constraints on prices in from Scandinavian economies (c.f. Renkin and Züllig 2024, Bauer et al. 2026), the customer-market channel seems far more plausible than the working-capital channel.

Table D.3: Impact of Credit Supply Shocks on Credit Market Outcomes

	(1)	(2)	(3)
CSS	-4.37*** (1.33)	36.10* (18.73)	
CSS (Low Irrev)			-6.54*** (2.28)
CSS (High Irrev)			-3.40** (1.63)
High-Low Sig. Diff.			N
Observations	4,365	222	4,100

Notes: Column (1) reports the effect of a credit tightening on the probability of obtaining a new loan or a favorable modification. Column (2) estimates the effect of tighter credit supply on the change in the all-in-drawn loan spread (basis points) between a borrower's last pre-Lehman loan and a loan signed over 2008:Q4-2009:Q2. Column (3) repeats (1) but splits the sample by whether the borrower's industry has above- or below-median irreversibility measured by irreversibility. Controls and fixed effects follow [Chodorow-Reich \(2014\)](#). Column (3) saturates controls and fixed effects by the indicator for above/below median irreversibility. Standard errors clustered by primary lender in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E Omitted Proofs for the PE 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.

E.1 Setup

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

$$y_0 = p_0^{-\eta}, \quad y_1^z = (p_1^z)^{-\eta} \mathcal{H}(y_0 \mid z), \quad \mathcal{H}(y_0 \mid z) \equiv z + \chi y_0^{\tilde{\theta}}, \quad (\text{E.1})$$

where $\mathcal{H}(y_0 \mid z)$ is the level of $t = 1$ demand in state $z \in \{B, G\}$, with $0 < B < G$, each state having probability $1/2$. Its slope in y_0 ,

$$\mathcal{H}'(y_0) \equiv \chi \tilde{\theta} y_0^{\tilde{\theta}-1} \geq 0, \quad (\text{E.2})$$

is the same in both states.

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 $k_1^z = (1 - \delta)k_0 + i_1^z$. Net capital expenditure in the morning of $t = 1$ is

$$\Phi_\kappa(i) \equiv \max\{i, (1 - \kappa)i\}, \quad (\text{E.3})$$

which equals i when the firm invests and $(1 - \kappa)i$ when it disinvests. Dividends are

$$d_0 = p_0 y_0 - w \ell_0, \quad d_1^z = p_1^z y_1^z - w \ell_1^z - \Phi_\kappa(i_1^z), \quad (\text{E.4})$$

and the firm maximizes (2). The model ends after the afternoon of $t = 1$, so capital left at that point has no value.

Choices. At $t = 0$ the firm chooses y_0 , which pins down $p_0 = y_0^{-1/\eta}$ and ℓ_0 . In the morning of $t = 1$ it observes z and chooses k_1^z . In the afternoon it chooses y_1^z . Since y_1^z does not affect demand in any later period, the afternoon choice is static.

Parameter Restrictions. Throughout, $\eta > 1$, $\alpha, \delta \in (0, 1)$, $\kappa \in [0, 1]$, $w, R, k_0, \varphi > 0$, $\chi \geq 0$, and $\tilde{\theta} \in [0, 1)$. Propositions 2.1 and 2.2 concern the model with customer markets, $\chi\tilde{\theta} > 0$; when $\chi\tilde{\theta} = 0$, $\mathcal{H}$ does not depend on y_0 . A strict sale of capital requires $\kappa < 1$, since at $\kappa = 1$ a sale returns nothing; the hypotheses of Proposition 2.2 imply this.

E.2 Static Block

Within any period, we can solve out the labor choice and determine output/profits as a function of the chosen markup over marginal cost, $\mu \equiv p/mc$. From the production function,

$$C(y, k) \equiv w \left(\frac{y}{k^\alpha} \right)^{\frac{1}{1-\alpha}} = w y^{\frac{1}{1-\alpha}} k^{-\frac{\alpha}{1-\alpha}}, \quad mc(y, k) \equiv \frac{\partial C}{\partial y} = \frac{w}{1-\alpha} y^{\frac{\alpha}{1-\alpha}} k^{-\frac{\alpha}{1-\alpha}}. \quad (\text{E.5})$$

Also define

$$\tilde{\alpha}_k \equiv \frac{\alpha(\eta - 1)}{1 + \alpha(\eta - 1)} \in (0, 1), \quad (\text{E.6})$$

which satisfies

$$1 - \tilde{\alpha}_k = \frac{1}{1 + \alpha(\eta - 1)}, \quad (\text{E.7})$$

$$\tilde{\alpha}_k = \alpha(\eta - 1)(1 - \tilde{\alpha}_k). \quad (\text{E.8})$$

Lemma E.1. *Given the demand shifter $H = \mathcal{H}(h \mid z)$, the capital stock k , and the markup μ , sales and operating profit are*

$$y = \mathcal{B}(\mu) H^{(1-\alpha)(1-\tilde{\alpha}_k)} k^{\eta\alpha(1-\tilde{\alpha}_k)}, \quad \mathcal{B}(\mu) = \left[\frac{1-\alpha}{w\mu} \right]^{\eta(1-\alpha)(1-\tilde{\alpha}_k)}, \quad (\text{E.9})$$

$$\Pi = \mathcal{A}(\mu) H^{1-\tilde{\alpha}_k} k^{\tilde{\alpha}_k}, \quad \mathcal{A}(\mu) = \left(1 - \frac{1-\alpha}{\mu} \right) \left[\frac{1-\alpha}{w\mu} \right]^{(\eta-1)(1-\alpha)(1-\tilde{\alpha}_k)}, \quad (\text{E.10})$$

where the two exponents in (E.9) sum to one. $\mathcal{B}$ is strictly decreasing, and $\mathcal{A}$ is single-peaked at the static markup $\bar{\mu} = \eta/(\eta-1)$, with $\bar{A} \equiv \mathcal{A}(\bar{\mu})$, so that $\mathcal{A}'(\mu) > 0$ exactly on $(0, \bar{\mu})$.

Proof. Setting $mc(y, k) = p/\mu$ with $p = H^{1/\eta} y^{-1/\eta}$ in (E.5) gives $y^{\frac{\alpha}{1-\alpha} + \frac{1}{\eta}} = \frac{1-\alpha}{w\mu} H^{1/\eta} k^{\frac{\alpha}{1-\alpha}}$. The exponent on y is $\frac{1+\alpha(\eta-1)}{\eta(1-\alpha)} = \frac{1}{\eta(1-\alpha)(1-\tilde{\alpha}_k)}$, which gives (E.9). Then $\Pi = py - w\ell = py \left(1 - \frac{1-\alpha}{\mu} \right)$ by the last equality in (E.5), and $py = H^{1/\eta} y^{1-1/\eta}$. The exponent on k is $\eta\alpha(1-\tilde{\alpha}_k)\frac{\eta-1}{\eta} = \tilde{\alpha}_k$ by (E.6), and the exponent on H is $\frac{1}{\eta} [1 + (1-\alpha)(\eta-1)(1-\tilde{\alpha}_k)] = 1 - \tilde{\alpha}_k$, giving (E.10). For the peak, $\mathcal{A} \propto \mu^{-a} \left(1 - \frac{1-\alpha}{\mu} \right)$ with $a \equiv (\eta-1)(1-\alpha)(1-\tilde{\alpha}_k)$, and $\mathcal{A}' = 0$ at $\mu = (1-\alpha)(1+a)/a = \eta/(\eta-1)$ since $1+a = \eta(1-\tilde{\alpha}_k)$. $\square$

Differentiating $\mathcal{B}$ in (E.9) gives

$$-\mathcal{B}'(\mu) = (1-\alpha)\eta(1-\tilde{\alpha}_k) \frac{\mathcal{B}(\mu)}{\mu}. \quad (\text{E.11})$$

I will use this expression below.

Problem in $t = 2$. Because $t = 2$ is terminal, the firm behaves statically and does not need to choose k_2 nor h_2 . The $t = 2$ markup is $\bar{\mu}$ and $t = 2$ operating profit is $\bar{A} (H_1^z)^{1-\tilde{\alpha}_k} k_1^{\tilde{\alpha}_k}$.

E.3 Optimal Capital Choice in $t = 1$ and Terminal Returns

Write $\tilde{A} \equiv \bar{A}/R$ for $t = 2$ profit per unit of $(H_1^z)^{1-\tilde{\alpha}_k} k_1^{\tilde{\alpha}_k}$ discounted to $t = 1$, and define

$$\hat{k}(p^I) \equiv \left[\frac{\tilde{\alpha}_k \tilde{A}}{p^I} \right]^{\frac{1}{1-\tilde{\alpha}_k}}, \quad (\text{E.12})$$

so that $H \hat{k}(p^I)$ is the level of $t = 2$ capital at which its discounted marginal product equals the price p^I of the investment good. Given the $t = 2$ demand shifter H and the capital k_0 carried into $t = 1$, the choice of k_1 solves

$$V_2(H, k_0; \kappa) \equiv \max_{k_1 \geq 0} \left\{ \tilde{A} H^{1-\tilde{\alpha}_k} k_1^{\tilde{\alpha}_k} - (k_1 - (1 - \delta_k)k_0)^+ + (1 - \kappa) ((1 - \delta_k)k_0 - k_1)^+ \right\}, \quad (\text{E.13})$$

where $(x)^+ \equiv \max\{x, 0\}$. The terminal value of the firm depends on z through H , hence the lack of a superscript in (E.13). The marginal product of k_1 is strictly decreasing, and the cost of capital has slope 1 above $(1 - \delta_k)k_0$ and $1 - \kappa$ below it, so

$$k_1^*(H, k_0; \kappa) = \begin{cases} H \hat{k}(1), & (1 - \delta_k)k_0 \leq H \hat{k}(1) \quad (\text{buy}), \\ (1 - \delta_k)k_0, & H \hat{k}(1) < (1 - \delta_k)k_0 < H \hat{k}(1 - \kappa) \quad (\text{inaction}), \\ H \hat{k}(1 - \kappa), & (1 - \delta_k)k_0 \geq H \hat{k}(1 - \kappa) \quad (\text{sell}). \end{cases} \quad (\text{E.14})$$

The firm buys when demand is high relative to its inherited capital, sells when demand is low, and is inactive in between, where a marginal sale at $1 - \kappa$ would lose more than it saves. Assumption ?? of the main text is the statement that the bad state lies in the selling region and the good state in the buying region:

$$\mathcal{H}(h_1^B \mid z_B) \hat{k}(1 - \kappa) < (1 - \delta_k)k_0 < \mathcal{H}(h_1^G \mid z_G) \hat{k}(1). \quad (\text{E.15})$$

Lemma E.2. *Under Assumption ??, the terminal value is affine in the two stocks, $V_2^z = R_k^z k_0 + R_H^z H$, with returns*

$$R_k^G = 1 - \delta_k, \quad R_k^B = (1 - \kappa)(1 - \delta_k), \quad R_H^G = \bar{R}_H, \quad R_H^B = \bar{R}_H (1 - \kappa)^{-\frac{\tilde{\alpha}_k}{1 - \tilde{\alpha}_k}}, \quad (\text{E.16})$$

where $\bar{R}_H \equiv (1 - \tilde{\alpha}_k) \tilde{A} \left[\tilde{\alpha}_k \tilde{A} \right]^{\frac{\tilde{\alpha}_k}{1 - \tilde{\alpha}_k}}$. In both states $R_H^z = (1 - \tilde{\alpha}_k) \tilde{A} (\hat{k}^z)^{\tilde{\alpha}_k}$ and $R_k^z = (1 - \delta_k) \tilde{\alpha}_k \tilde{A} (\hat{k}^z)^{-(1 - \tilde{\alpha}_k)}$, where $\hat{k}^z \equiv k_1^*/H_1^z$ is the terminal capital per unit of demand, equal to $\hat{k}(1)$ in G and $\hat{k}(1 - \kappa)$ in B .

Proof. In the buy and sell regions the firm trades at a constant price p^I (1 or $1 - \kappa$), so $V_2 = \max_{k_1} \{ \tilde{A} H^{1 - \tilde{\alpha}_k} k_1^{\tilde{\alpha}_k} - p^I k_1 \} + p^I (1 - \delta_k) k_0$. The first-order condition gives $k_1 = H \hat{k}(p^I)$, and substituting back,

$$\max_{k_1} \left\{ \tilde{A} H^{1 - \tilde{\alpha}_k} k_1^{\tilde{\alpha}_k} - p^I k_1 \right\} = H \hat{k}(p^I)^{\tilde{\alpha}_k} \left[\tilde{A} - p^I \hat{k}(p^I)^{1 - \tilde{\alpha}_k} \right] = (1 - \tilde{\alpha}_k) \tilde{A} \hat{k}(p^I)^{\tilde{\alpha}_k} H, \quad (\text{E.17})$$

using $p^I \hat{k}(p^I)^{1 - \tilde{\alpha}_k} = \tilde{\alpha}_k \tilde{A}$ from (E.12). Hence $R_H = (1 - \tilde{\alpha}_k) \tilde{A} \hat{k}(p^I)^{\tilde{\alpha}_k}$ and $R_k = p^I (1 - \delta_k)$. Evaluating at $p^I = 1$ and $p^I = 1 - \kappa$ gives (E.16), and $\tilde{\alpha}_k \tilde{A} \hat{k}(p^I)^{-(1 - \tilde{\alpha}_k)} = p^I$ gives the second expression for R_k^z . $\square$

Two derivatives of the returns in κ are used below:

$$\frac{\partial R_k^B}{\partial \kappa} = -(1 - \delta_k), \quad \frac{\partial R_H^B}{\partial \kappa} = \hat{k}(1 - \kappa), \quad \frac{\partial R_k^G}{\partial \kappa} = \frac{\partial R_H^G}{\partial \kappa} = 0. \quad (\text{E.18})$$

The first derivative and the last two are read off (E.16). For the second, $R_H^B = (1 - \tilde{\alpha}_k) \tilde{A} \hat{k}(1 - \kappa)^{\tilde{\alpha}_k}$ by Lemma E.2, $\hat{k}'(p^I) = -\hat{k}(p^I)/[(1 - \tilde{\alpha}_k)p^I]$ by (E.12), and $\tilde{\alpha}_k \tilde{A} \hat{k}(p^I)^{\tilde{\alpha}_k - 1} = p^I$ by the

first-order condition $p^I \widehat{k}(p^I)^{1-\tilde{\alpha}_k} = \tilde{\alpha}_k \tilde{A}$ of (E.12), so

$$\begin{aligned} \frac{\partial R_H^B}{\partial \kappa} &= (1 - \tilde{\alpha}_k) \tilde{A} \tilde{\alpha}_k \widehat{k}(1 - \kappa)^{\tilde{\alpha}_k - 1} \cdot \frac{\widehat{k}(1 - \kappa)}{(1 - \tilde{\alpha}_k)(1 - \kappa)} \\ &= \tilde{\alpha}_k \tilde{A} \widehat{k}(1 - \kappa)^{\tilde{\alpha}_k - 1} \frac{\widehat{k}(1 - \kappa)}{1 - \kappa} = (1 - \kappa) \frac{\widehat{k}(1 - \kappa)}{1 - \kappa} = \widehat{k}(1 - \kappa). \end{aligned}$$

Irreversibility affects the terminal block only in the bad state, and there it does two things: it lowers the return on inherited capital, $R_k^B = (1 - \kappa)(1 - \delta_k)$, and it raises the return on the customer base, R_H^B . The second effect arises because the firm keeps more capital per unit of demand when selling is costly, $\widehat{k}(1 - \kappa) > \widehat{k}(1)$, and a larger customer base is worth more when more capital is available since it reduces future marginal cost.

E.4 Optimal Production in $t = 1$

The previous section determined the optimal capital choice k_1 , and after accounting for that choice, we can write the terminal value as $V_2^z = R_k^z k_0 + R_H^z H$ by Lemma E.2. What remains of the $t = 1$ problem is the optimal production level.

At $t = 1$ the state z is known. The firm solves

$$V(h_0, k_0 \mid z; \kappa) = \max_{\mu, y_1, h_1} \left\{ \mathcal{A}(\mu)(H_0^z)^{1-\tilde{\alpha}_k} k_0^{\tilde{\alpha}_k} + V_2(H_1^z, k_0; \kappa) \right\} \quad (\text{E.19})$$

subject to

$$y_1 = \mathcal{B}(\mu)(H_0^z)^{(1-\alpha)(1-\tilde{\alpha}_k)} k_0^{\eta\alpha(1-\tilde{\alpha}_k)}, \quad (\text{E.20})$$

$$h_1 = \rho_h h_0 + (1 - \rho_h) \vartheta_1^z y_1. \quad (\text{E.21})$$

Attaching multipliers λ_y^z and λ_h^z to (E.20) and (E.21), the first-order conditions are

$$\mu : \mathcal{A}'(\mu^z)(H_0^z)^{1-\tilde{\alpha}_k} k_0^{\tilde{\alpha}_k} + \lambda_y^z \mathcal{B}'(\mu^z)(H_0^z)^{(1-\alpha)(1-\tilde{\alpha}_k)} k_0^{\eta\alpha(1-\tilde{\alpha}_k)} = 0, \quad (\text{E.22})$$

$$y_1 : \lambda_y^z = (1 - \rho_h) \vartheta_1^z \lambda_h^z, \quad (\text{E.23})$$

$$h_1 : \lambda_h^z = R_H^z \mathcal{H}'(h_1^z), \quad (\text{E.24})$$

using $\partial V_2 / \partial H = R_H^z$ from Lemma E.2. Substituting (E.23) and (E.24) into (E.22) and dividing by $(H_0^z)^{1-\tilde{\alpha}_k} k_0^{\tilde{\alpha}_k}$ leaves $(H_0^z)^{-\alpha(1-\tilde{\alpha}_k)} k_0^{\alpha(1-\tilde{\alpha}_k)}$ on the second term, by (E.6), so

$$\frac{\mathcal{A}'(\mu^z)}{-\mathcal{B}'(\mu^z)} = (1 - \rho_h) \vartheta_1^z R_H^z \mathcal{H}'(h_1^z) \left(\frac{k_0}{H_0^z} \right)^{\alpha(1-\tilde{\alpha}_k)} > 0. \quad (\text{E.25})$$

Since $-\mathcal{B}' > 0$, (E.25) implies $\mathcal{A}'(\mu^z) > 0$, and by Lemma E.1

$$\mu^z < \bar{\mu}. \quad (\text{E.26})$$

Thus, the firm prices below the static optimum in $t = 1$ to build the customer base.

F Inventory Microfoundation

In this section, I describe a microfoundation for inventories based on Wen (2011). This microfoundation also leads to a reduced-form representation in which the stock of available goods are transformed into sales according to a function $\Gamma(z)$, where z is the share of the available goods that are kept as inventories.

F.1 Setup

The firm does not directly produce output q_t but instead assembles it from a continuum of parts. Let $x_{i,t}$ denote planned production of variety i before the idiosyncratic stock-out

shock is realized. Aggregate production is then

$$q_t = \left[\int_0^1 \tilde{z}_{n,i,t} x_{i,t}^{\varrho_n} di \right]^{1/\varrho_n}, \quad \varrho_n \in (0, 1), \quad (\text{F.1})$$

where $\tilde{z}_{n,i,t}$ is an i.i.d. idiosyncratic shock to the productivity of variety i , drawn from a Pareto distribution with CDF $F(\tilde{z}_n) = 1 - \tilde{z}_n^{-\zeta}$ on $[1, \infty)$, tail parameter $\zeta > 1$, and the standard regularity condition $\zeta(1 - \varrho_n) > 1$ which ensures finite aggregates. Crucially, the firm chooses variety-level production $x_{i,t}$ *before* the realization of $\tilde{z}_{n,i,t}$. This timing assumption makes inventory valuable as a way to avoid costly stock outs.

Optimal Stock-Out Cutoff. Let $n_{i,t-1}$ denote beginning-of-period inventories of variety i and $y_{i,t}$ denote sold output of that variety. By symmetry, each variety enters the period with the same available stock, equal to $x_{i,t} + n_{i,t-1}$. The firm chooses a Pareto cutoff $z_{n,t}^* \geq 1$ that partitions varieties into two regimes:

- *Stock-out* ($\tilde{z}_{n,i,t} \geq z_{n,t}^*$): the variety's effective demand exceeds available stock, so all available stock is sold, $y_{i,t} = x_{i,t} + n_{i,t-1}$, and $n_{i,t} = 0$.
- *Excess supply* ($\tilde{z}_{n,i,t} < z_{n,t}^*$): only a share of available stock is sold, $y_{i,t} < x_{i,t} + n_{i,t-1}$, and the residual becomes inventory $n_{i,t}$.

The lower $z_{n,t}^*$ is, the less inventory that the firm accumulates.

Aggregation. This section derives aggregate products sold and inventory accumulated.

It will be useful to define a few terms first:

$$D(z_n^*) \equiv \int_1^{z_n^*} \tilde{z}_n^{\frac{1}{1-\varrho_n}} dF(\tilde{z}_n) + (z_n^*)^{\frac{1}{1-\varrho_n}} [1 - F(z_n^*)], \quad (\text{F.2})$$

$$H(z_n^*) \equiv \int_1^{z_n^*} \left[(z_n^*)^{\frac{1}{1-\varrho_n}} - \tilde{z}_n^{\frac{1}{1-\varrho_n}} \right] dF(\tilde{z}_n), \quad (\text{F.3})$$

$$G(z_n^*) \equiv \int_1^{z_n^*} \tilde{z}_n^{\frac{1}{1-\varrho_n}} dF(\tilde{z}_n) + (z_n^*)^{\frac{\varrho_n}{1-\varrho_n}} \int_{z_n^*}^{\infty} \tilde{z}_n dF(\tilde{z}_n), \quad (\text{F.4})$$

with $D(z_n^*) + H(z_n^*) = (z_n^*)^{\frac{1}{1-\varrho_n}}$. When $\tilde{z}_n$ is Pareto-distributed, [Lenzu et al. \(accepted\)](#) shows⁵¹

$$G(z_n^*) = \frac{\zeta}{\frac{1}{1-\varrho_n} - \zeta} \left((z_n^*)^{\frac{1}{1-\varrho_n} - \zeta} - 1 \right) + \frac{\zeta}{\zeta - 1} (z_n^*)^{\frac{1}{1-\varrho_n} - \zeta}, \quad (\text{F.5})$$

$$D(z_n^*) = \left(1 + \frac{\zeta}{\frac{1}{1-\varrho_n} - \zeta} \right) (z_n^*)^{\frac{1}{1-\varrho_n} - \zeta} - \frac{\zeta}{\frac{1}{1-\varrho_n} - \zeta}, \quad (\text{F.6})$$

$$H(z_n^*) = (z_n^*)^{\frac{1}{1-\varrho_n}} \left(1 - (z_n^*)^{-\zeta} \right) - \frac{\zeta}{\frac{1}{1-\varrho_n} - \zeta} \left((z_n^*)^{\frac{1}{1-\varrho_n} - \zeta} - 1 \right). \quad (\text{F.7})$$

Using these expressions, define

$$\tilde{G}(z_n^*) \equiv \frac{G(z_n^*)^{1/\varrho_n}}{(z_n^*)^{\frac{1}{1-\varrho_n}}}, \quad \tilde{H}(z_n^*) \equiv \frac{H(z_n^*)}{(z_n^*)^{\frac{1}{1-\varrho_n}}}, \quad \tilde{\Phi}(z_n^*) \equiv \tilde{G}(z_n^*) - \frac{\tilde{G}'(z_n^*)}{\tilde{H}'(z_n^*)} \tilde{H}(z_n^*), \quad (\text{F.8})$$

so that

$$y_t = \tilde{G}(z_{n,t}^*)(q_t + n_{t-1}), \quad n_t = \tilde{H}(z_{n,t}^*)(q_t + n_{t-1}). \quad (\text{F.9})$$

Lemma F.1. *With $\tilde{G}, \tilde{H}$ as in (F.8), for every $z_n^* > 1$, $\tilde{G}'(z_n^*) < 0$ and $\tilde{H}'(z_n^*) > 0$.*

Proof. To prove the claim, I differentiate the definitions in (F.8). First, note that $\zeta(1 - \varrho_n) > 1$ implies $\zeta - \frac{1}{1-\varrho_n} > 0$. It follows that $G'(z_n^*) > 0$. Also, let

$$C_1 \equiv \zeta - \frac{1}{1 - \varrho_n} > 0, \quad C_2 \equiv \frac{\varrho_n}{(1 - \varrho_n)(\zeta - 1)} \in (0, 1).$$

Rewrite $\tilde{G}(z_n^*)$ as

$$\tilde{G}(z_n^*) = \left(\frac{\zeta}{C_1} \right)^{1/\varrho_n} (z_n^*)^{-\frac{\zeta-1}{\varrho_n}} \left((z_n^*)^{C_1} - C_2 \right)^{1/\varrho_n}.$$

Direct differentiation gives

$$\tilde{G}'(z_n^*) = -\frac{1}{1 - \varrho_n} \left(\frac{\zeta}{C_1} \right)^{1/\varrho_n} (z_n^*)^{-\frac{\zeta-1}{\varrho_n} - 1} \left((z_n^*)^{C_1} - C_2 \right)^{\frac{1-\varrho_n}{\varrho_n}} \left((z_n^*)^{C_1} - 1 \right).$$

⁵¹As notation, I use ζ and ϱ_n while [Lenzu et al. \(accepted\)](#) uses ξ and ρ , respectively.

For every $z_n^* > 1$, each factor on the right-hand side is positive except for the leading minus sign, because $C_1 > 0$, $C_2 < 1$, and hence $(z_n^*)^{C_1} - C_2 > (z_n^*)^{C_1} - 1 > 0$. Therefore $\tilde{G}'(z_n^*) < 0$.

For $\tilde{H}$, first note that

$$H'(z_n^*) = \frac{1}{1 - \varrho_n} (z_n^*)^{\frac{1}{1-\varrho_n}-1} (1 - (z_n^*)^{-\zeta}).$$

Then use the displayed derivative formula together with the identity $D(z_n^*) + H(z_n^*) = (z_n^*)^{1/(1-\varrho_n)}$.

$$\begin{aligned} \tilde{H}'(z_n^*) &= \frac{H'(z_n^*)}{(z_n^*)^{1/(1-\varrho_n)}} - \frac{H(z_n^*)}{(z_n^*)^{1/(1-\varrho_n)+1}} \cdot \frac{1}{1 - \varrho_n} \\ &= \frac{1}{(1 - \varrho_n)(z_n^*)^{1/(1-\varrho_n)+1}} \left[(z_n^*)^{1/(1-\varrho_n)} (1 - (z_n^*)^{-\zeta}) - H(z_n^*) \right] \\ &= \frac{1}{(1 - \varrho_n)(z_n^*)^{1/(1-\varrho_n)+1}} \left[D(z_n^*) - (z_n^*)^{1/(1-\varrho_n)-\zeta} \right]. \end{aligned}$$

By the definition of D in (F.2),

$$D(z_n^*) - (z_n^*)^{1/(1-\varrho_n)-\zeta} = \int_1^{z_n^*} \tilde{z}_n^{1/(1-\varrho_n)} dF(\tilde{z}_n),$$

which is positive if and only if $z_n^* > 1$, and zero if $z_n^* = 1$. □

F.2 Deriving the Reduced-Form Specification

Since $\tilde{H}(z_n^*)$ is strictly increasing on $z_n^* > 1$ with $\tilde{H}(1) = 0$, the map $z_n^* \mapsto z \equiv \tilde{H}(z_n^*)$ is a monotone bijection. Let $z_n^*(z)$ denote its inverse. I can now define

$$\Gamma(z) \equiv \tilde{G}(z_n^*(z)). \tag{F.10}$$

Lemma F.2 (Strict monotonicity and concavity of Γ). *The function $\Gamma(z)$, defined by (F.10)*

for $z \in [0, 1)$, is strictly decreasing and strictly concave. Further, the function satisfies

$$\Gamma'(z) = \frac{\tilde{G}'(z_n^*(z))}{\tilde{H}'(z_n^*(z))},$$

$$\Gamma'(1) = - \left(\frac{\zeta}{\zeta - \frac{1}{1-\varrho_n}} \right)^{\frac{1}{\varrho_n}-1} < 0.$$

Proof. It will be useful to define

$$C_1 \equiv \zeta - \frac{1}{1-\varrho_n} > 0, \quad C_2 \equiv \frac{\varrho_n}{(1-\varrho_n)(\zeta-1)} \in (0, 1),$$

where the inequalities follow from $\zeta(1-\varrho_n) > 1$. Note that these coefficients are the same as in the proof of Lemma F.1. Then

$$\tilde{G}(z_n^*) = \left(\frac{\zeta}{C_1} \right)^{1/\varrho_n} (z_n^*)^{-\frac{\zeta-1}{\varrho_n}} ((z_n^*)^{C_1} - C_2)^{1/\varrho_n}, \quad (\text{F.11})$$

$$\tilde{H}(z_n^*) = 1 + \frac{(z_n^*)^{-\zeta} - \zeta(1-\varrho_n)(z_n^*)^{-1/(1-\varrho_n)}}{\zeta(1-\varrho_n) - 1}, \quad (\text{F.12})$$

$$\tilde{H}'(z_n^*) = \frac{\zeta}{\zeta(1-\varrho_n) - 1} (z_n^*)^{-\zeta-1} ((z_n^*)^{C_1} - 1) > 0. \quad (\text{F.13})$$

$$\tilde{G}'(z_n^*) = -\frac{1}{1-\varrho_n} \left(\frac{\zeta}{C_1} \right)^{1/\varrho_n} (z_n^*)^{-\frac{\zeta-1}{\varrho_n}-1} ((z_n^*)^{C_1} - C_2)^{\frac{1-\varrho_n}{\varrho_n}} ((z_n^*)^{C_1} - 1) < 0. \quad (\text{F.14})$$

Hence $\tilde{H}(z_n^*) \uparrow 1$ as $z_n^* \rightarrow \infty$, so the transformed inventory choice satisfies $z \in [0, 1)$. Lemma F.1 and (F.12) imply that $z_n^* \mapsto z = \tilde{H}(z_n^*)$ is a bijection from $[1, \infty)$ onto $[0, 1)$, with inverse $z_n^*(z)$. Using $z = \tilde{H}(z_n^*)$ and $\Gamma(z) = \tilde{G}(z_n^*(z))$, the chain rule gives

$$\Gamma'(z) = \frac{\tilde{G}'(z_n^*(z))}{\tilde{H}'(z_n^*(z))} = -C_3 (z_n^*(z))^{-C_4} ((z_n^*(z))^{C_1} - C_2)^{C_5} < 0, \quad (\text{F.15})$$

where

$$C_3 \equiv \frac{C_1}{\zeta} \left(\frac{\zeta}{C_1} \right)^{1/\varrho_n} > 0, \quad C_4 \equiv \frac{(1-\varrho_n)C_1}{\varrho_n}, \quad C_5 \equiv \frac{1-\varrho_n}{\varrho_n} > 0.$$

Note that this expression proves the displayed derivative formula in the lemma. Also, $z \uparrow 1$ if and only if $z_n^*(z) \rightarrow \infty$, so using $C_4 = C_5 C_1$ we may rewrite (F.15) as

$$\Gamma'(z) = -C_3 \left(1 - \frac{C_2}{(z_n^*(z))^{C_1}} \right)^{C_5}.$$

Therefore,

$$\Gamma'(1) \equiv \lim_{z \uparrow 1} \Gamma'(z) = -C_3 = - \left(\frac{\zeta}{C_1} \right)^{1/\varrho_n - 1} = - \left(\frac{\zeta}{\zeta - \frac{1}{1-\varrho_n}} \right)^{\frac{1}{\varrho_n} - 1} < 0.$$

Differentiating (F.15) with respect to z_n^* gives

$$\frac{d}{dz_n^*} \Gamma' \left(\tilde{H}(z_n^*) \right) = -C_3 (z_n^*)^{-C_4 - 1} \left((z_n^*)^{C_1} - C_2 \right)^{C_5 - 1} \left[-C_4 \left((z_n^*)^{C_1} - C_2 \right) + C_5 C_1 (z_n^*)^{C_1} \right].$$

Since $C_4 = C_5 C_1$, this simplifies to

$$\frac{d}{dz_n^*} \Gamma' \left(\tilde{H}(z_n^*) \right) = -C_3 C_5 C_1 C_2 (z_n^*)^{-C_4 - 1} \left((z_n^*)^{C_1} - C_2 \right)^{C_5 - 1} < 0.$$

Since $dz/dz_n^* = \tilde{H}'(z_n^*) > 0$, another application of the chain rule yields

$$\Gamma''(z) = \frac{1}{\tilde{H}'(z_n^*(z))} \frac{d}{dz_n^*} \Gamma' \left(\tilde{H}(z_n^*(z)) \right) < 0 \quad \text{for every } z \in (0, 1). \quad (\text{F.16})$$

Equations (F.15) and (F.16) therefore imply that Γ is strictly decreasing and strictly concave on $[0, 1)$. □