

THE EFFECT OF THE CREDIT CRUNCH ON OUTPUT PRICE DYNAMICS:
THE CORPORATE INVENTORY AND LIQUIDITY MANAGEMENT CHANNEL*

RYAN KIM[†]

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I study how a credit crunch affects output price dynamics. I build a unique micro-level dataset that combines scanner-level prices and quantities with producer information, including the producer's banking relationships, inventory, and cash holdings. I exploit the Lehman Brothers' failure as a quasi-experiment and find that the firms that face a negative credit supply shock decrease their output prices approximately 15% more than their unaffected counterparts. I hypothesize that such firms reduce prices to liquidate inventory and to generate additional cash flow from the product market. I find strong empirical support for this hypothesis: (i) the firms that face a negative bank shock temporarily decrease their prices and inventory and increase their market share and cash holdings relative to their counterparts, and (ii) this effect is stronger for the firms and sectors with a high initial inventory or small initial cash holdings. *JEL Codes:* E31, E32, E44, G01, G31, G33, L11.

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[†]Johns Hopkins University, rkim59@jhu.edu

I INTRODUCTION

The questions of how and the extent to which credit market disruptions affect firms' economic decisions have been of vital interest in the economics and finance literature, particularly after the 2007-2009 financial crisis. This period was characterized not only by a significant drop in total output and employment but also by a dysfunctional credit market. At the peak of the credit market stress following the September 2008 failure of Lehman Brothers, new loans to large borrowers dropped 79% relative to the level of new loans to large borrowers in the credit boom period (Ivashina and Scharfstein, 2010). The TED spread, an indicator of perceived credit risk, surpassed 300 basis points after the Lehman failure, which broke the previous record set after the 1987 Black Monday crash.

During these credit market disruptions, the producer price index plummeted approximately 15% in three months.¹ Given this aggregate correlation, this article seeks to answer the following questions: Do the firms that face a negative credit supply shock decrease their output prices? If so, why do they decrease their output prices?

Identification poses the biggest challenge in answering these questions. Although there was a clear positive correlation between inflation and credit market conditions during the financial crisis, it is difficult to identify the true relationship between these two factors from the aggregate data. The aggregate correlation is based on the Great Recession, and without relying on credit market conditions, conventional macroeconomic models can easily explain a decrease in inflation during the recession. Even worse, many influential events, such as a fall in housing prices (Mian, Rao, and Sufi 2013), a drop in oil prices (Hamilton 2009), and a decrease in international trade (Eaton et al. 2016), occurred at the same time, which makes aggregate time-series comparisons nearly impossible.

To overcome this identification challenge, I build a novel micro-level dataset that combines the following: the producers' prices and sales at the barcode level from the Nielsen Homescan Panel database; the producers' balance sheet information from the Orbis database; and the producers' loan market access from the Dealscan database. The merged dataset contains detailed information on prices and quantities sold by public and private firms and the producers' banking relationships from 2004 to 2011. For example, if a household purchases Coke at a store, then I observe the price and quantity of the Coke purchased, Coca-Cola's balance sheet, and which bank Coca-Cola deals with. To the best of my knowledge, this paper is the first to combine information on the producers' price and quantity with information on their banking relationships.

Armed with detailed micro-level data, I exploit the "bank shock" at the time of the Lehman failure and find that the firms that face a negative credit supply shock *decrease* their output prices approximately 15% more than their unaffected counterparts. Although these micro-level data provide rich cross-sectional variation in addition to time-series variation, they do not automatically solve the identification problem because of the difficulty in identifying credit-constrained firms in the data. Farre-Mensa and Ljungqvist (2016) test conventional micro-level financial constraint measures such as Kaplan-Zingales (Kaplan and

1. See Online Appendix S3. This price movement partially reflects a fall in oil and commodity prices in this period, and I discuss the relationship between the change in commodity prices and the mechanism proposed in the article in explaining the aggregate inflation dynamics.

Zingales 1997) and Whited-Wu (Whited and Wu 2006) and conclude that they do not accurately identify financially-constrained firms because they are constructed by using firm-level balance sheet variables that likely reflect company characteristics other than their level of financial constraint. Thus, instead of relying on firm-level balance sheet variables, to generate plausibly exogenous variation in firm-level credit supply conditions, I utilize a change in bank health at the time of the Lehman failure. In addition to my main measure of the change in bank health based on the banks' loan issuance, I use the following three bank shock measures from Chodorow-Reich (2014) that are not highly correlated with one another but provide consistent results: the banks' exposure to the Lehman failure; the banks' exposure to toxic asset-backed securities; and bank balance sheet items, such as bank deposits and net trading revenues that are unlikely to be correlated with borrowers' characteristics. These three measures affect the firms' credit supply conditions for reasons that are plausibly orthogonal to their characteristics related to pricing decisions.

I hypothesize that the firms that face a negative credit supply shock decrease their output prices by liquidating inventory and dumping their products to generate extra cash flow from the product market, and I provide strong empirical support for this hypothesis. By using micro-level data and a corresponding identification strategy, I find that the firms that face negative bank shocks decrease their inventory relative to their counterparts. These firms decrease their output prices only temporarily and then increase them after approximately one year; these actions indicate that firms temporarily liquidate their inventory because of a negative credit supply shock but cannot sell their inventory forever; thus, they must increase prices in the medium-run. Additionally, these firms increase their market share and cash holdings, which illustrates that they increase their cash flow by selling more to the product market as a result of lowering their output prices. Moreover, the effect on output prices is stronger for the firms or sectors that had larger inventories or smaller cash holdings before the Lehman failure, which confirms my hypothesis. From a corporate inventory and liquidity management perspective, this hypothesis can be interpreted to imply that companies convert illiquid assets (inventory) to liquid assets (cash) when their insurers (banks) cannot lend to them and that companies decrease their output prices in this conversion process.

Additionally, I estimate the heterogeneous treatment effects across firms and sectors and implement numerous robustness tests to gain additional insights from the data and to confirm the validity of the bank shock measures. I find that the firms that face negative bank shocks decrease their output prices more if (i) they face high product demand elasticity, (ii) they did not issue a bond before the credit supply shock was realized, (iii) they had to pay out loans immediately after the Lehman failure, (iv) they dealt with a small number of lead-lenders in the pre-Lehman period, or (v) they are small in terms of employment or total assets. The firms that face high demand elasticity are more likely to decrease their output prices when they face a negative credit supply shock because they can sell more products while experiencing a smaller decrease in output prices.² If demand elasticity is very low—such that products complement other products—then firms would not be able to cut output prices to increase revenue. Other results are also intuitive and consistent with

2. Of course, the firms that face high demand elasticity might have a smaller incentive to lower their prices if their goal is to generate a certain amount of revenue. Such companies would be able to make enough revenue by decreasing their prices by a small amount, whereas their counterparts must lower their prices more to earn the same amount of revenue. There are two opposing forces, and the empirical question of which effects dominate remains.

the literature since the effect of a credit supply shock is likely to be larger for the firms that do not have bond access (Becker and Ivashina 2014), that had to pay out loans after the Lehman failure (Almeida et al. 2012), or that are small (Gertler and Gilchrist 1994). Moreover, I undertake various additional empirical analyses to address the potential concerns that relate to retailer decisions, purchaser characteristics, variety-quality changes, external validity, changes in local conditions, foreign exposure, other price indexes, pre-trends, and sample weights.

My findings are surprising because they seemingly conflict with the influential work of Gilchrist et al. (2017), who, by using liquidity as a measure of financial constraint, find that financially-constrained firms *raise* their output prices. The underlying reason for this difference is the difference in the *measure* of financial constraint, which is the “weak liquidity position” in Gilchrist et al. (2017). The term “weak liquidity position” is used in their paper and refers to firms with a small amount of liquidity. I replicate their findings in my sample by using their measure of financial constraint—liquidity—to confirm that different results arise from the difference in the measure, not the sample or regression specification. Consistent with Gilchrist et al. (2017), the results are robust to using two alternative periods of the liquidity positions, namely, the contemporaneous period (the year 2008) and the lagged period (the year 2006).

A natural question is why different measures of financial constraint cause different results. Previous studies in the corporate finance literature raise concerns about using liquidity as a measure of financial constraint. In their study on liquidity position, Kahle and Stulz (2013) find that the firms that face a negative bank shock raised—rather than lowered—their liquidity in 2008.³ This result is consistent with my findings in Table V and with my hypothesis that such firms convert inventory (illiquid assets) to cash (liquid assets). The firms that suffer from a negative bank shock would therefore be classified as firms in a “strong liquidity position”, not a “weak liquidity position.” Regarding the lagged (2006) liquidity position, a seminal paper by Bates, Kahle, and Stulz (2009) identifies more than ten factors that lead firms to hold more liquid assets. In particular, they find that the “weak liquidity position” is associated with more investment, borrowing, acquisitions, and a stable cash flow—characteristics that likely reflect unconstrained companies rather than constrained companies. I confirm the findings of Bates, Kahle, and Stulz (2009) by using the year 2006’s liquidity position and find that controlling for such characteristics the impact of lagged liquidity on firm-level price changes signs and becomes insignificant. More generally, a vast body of literature in corporate finance asks why companies hold liquidity. Almeida et al. (2014) survey this literature and conclude that firms hold more liquidity because they are *more* likely to be financially constrained. This argument dates back to Keynes (1936), who discusses that there is a fundamental relationship between corporate liquidity management and financial friction and emphasizes the precautionary saving motive to explain the variation in the corporate liquidity position. Because of these concerns about using liquidity as a measure of financial constraint, I instead use bank shocks—which are not subject to this criticism—as proposed by Ivashina and Scharfstein (2010) and Chodorow-Reich (2014). See Section V and Online Appendix S7 for a more detailed discussion and empirical evidence on the reconciliation with the previous study.

More broadly, this article is related to the papers that study financially-constrained companies’ pricing

3. See, for example, Perez-Orive (2016) and Garcia-Macia and Villacorta (2019) for a theoretical formulation of such behavior.

decisions. Standard business cycle models with financial friction emphasize the cost-push channel—in which an increase in output prices is due to an increase in financial costs—or other channels that lead companies to increase their prices due to financial friction.⁴ However, this increase in output price will be inconsistent with the micro-level empirical evidence in this article. I seek to expand these previous studies by incorporating a fire sale inventory mechanism, which maintains consistency with the micro-level empirical evidence that I find and is also consistent with a sudden, dramatic, and temporary fall in inflation in this period; at the end of the analysis, I present the back-of-the-envelope calculation for the effect of the credit supply shock on aggregate inflation dynamics. Papers on industrial organization and corporate finance also study this topic, but they are inconclusive regarding how financial distress affects output prices, particularly at the aggregate level. Several papers on the airline industry find that financial distress leads to a decrease in output prices (Borenstein and Rose 1995; Phillips and Sertsiotis 2013), while other studies find the opposite result for retail industries (Chevalier 1995a,b; Chevalier and Scharfstein 1995, 1996). I complement this line of research by exploiting a new dataset with bank shocks that generate plausibly exogenous variations in the companies' credit supply conditions.

This paper emphasizes the importance of inventory and liquidity management in explaining the output price dynamics during the banking crisis and is closely related to previous studies on this topic. The most closely related papers to this study are the seminal work by Gertler and Gilchrist (1994) and Kashyap, Lamont, and Stein (1994), who provide evidence that liquidity-constrained firms liquidate their inventories.⁵ At the international-level, Alessandria, Kaboski, and Midrigan (2010b) document a close link among inventory, the price-cost markup, and the interest rate shock. In the business cycle research, inventory is known to contain valuable information because of its volatility and pro-cyclical behavior (Ramey and West 1999).⁶ In extending previous studies, I show that the bank shock, which has rarely been addressed in this literature, can generate pro-cyclical inflation and inventory dynamics.

For the empirical analysis, I use the bank shock to overcome the identification challenge. Previous studies document that the firms that cannot borrow from banks are likely to default (Khwaja and Mian 2008) and decrease their investment (Peek and Rosengren 1997, 2000; Amiti and Weinstein 2018), employment (Chodorow-Reich 2014; Greenstone, Mas, and Nguyen 2020), and exports (Amiti and Weinstein 2011; Paravisini et al. 2015). I show that such a shock has an essential effect on output price through the inventory and cash adjustment of firms.

The rest of this paper is structured as follows: Section II explains the construction and description of the micro-level data, credit supply shock, and price index. Section III presents the main reduced-form empirical

4. Papers such as Del Negro, Giannoni, and Schorfheide (2015), Christiano, Eichenbaum, and Trabandt (2015), and Gilchrist et al. (2017) incorporate financial friction into a business cycle model to explain inflation dynamics during the Great Recession.

5. Other papers, such as Carpenter, Fazzari, and Petersen (1994, 1998) and Bates, Kahle, and Stulz (2009), also suggest a close link between corporate inventory investment and internal finance (or the corporate cash position). My findings also complement the studies that examine how firms substitute between external financing and internal financing or between banks and cash (e.g., Sufi 2009; Lins, Servaes, and Tufano 2010; Campello et al. 2011).

6. Previous studies examine inventory dynamics and the sources of cyclical fluctuation (West 1990), the slope of marginal cost (Ramey 1991), price-cost markup cyclical (Bils and Kahn 2000; Kryvtsov and Midrigan 2013), international trade (Alessandria, Kaboski, and Midrigan 2010a, 2011), international business cycles (Alessandria, Kaboski, and Midrigan 2013), and news shocks (Crouzet and Oh 2016). Papers such as Fisher and Hornstein (2000) and Khan and Thomas (2007) incorporate inventory into the business cycle model to explain the salient feature of the data.

results. Section IV proposes the inventory adjustment hypothesis with empirical support, and Section V clarifies the relationship with Gilchrist et al. (2017). Section VI presents a streamlined discussion of a simple business cycle model, which considers aggregate dynamics. Section VII concludes.

II DATA DESCRIPTION AND MEASURE OF THE VARIABLES

II.A Data Description

A major novelty of this paper is that it constructs a micro-level dataset that integrates producers' output prices and quantities, their inventories and cash holdings, and their relationships with banks.

The price and quantity data originate from the ACNielsen Homescan Panel, which was made available by the Kilts Marketing Data Center at the University of Chicago Booth School of Business.⁷ The data contain approximately 1.7 million barcode-level product prices and quantities recorded daily from 55,000 households per year on average. A barcode is a unique universal product code (UPC) assigned to each product and is used to scan and store product information. The data begin in 2004 and end in 2011, which covers the period before, during, and after the financial panic of 2008. All households sampled by Nielsen are provided with in-home scanners to record their purchases of products with barcodes. Nielsen assigns a sample weight—or a projection factor—to each household based on ten demographic variables to make the sample nationally representative.⁸ According to Nielsen, the Homescan Panel covers approximately 30 percent of all household expenditures on goods in the consumer price index (CPI) basket. To confirm the validity of the data, Online Appendix S3.A shows that a scanner price index made from the Nielsen data closely follows the U.S. Bureau of Labor Statistics (BLS) official price index.

There are many advantages of using the ACNielsen database to identify the effect of credit supply shocks on output price dynamics. First, the database records product prices at the barcode level, which is likely to be the most granular way to define the product. This feature not only helps uncover the effects of the introduction and destruction of products on prices but also allows a comparison of similar products produced by the firms that face different degrees of a credit supply shock. Second, the dataset provides product sales information, which is useful for separating the quality component of product prices and for confirming that the effect is not driven by the change in product demand. Finally, the data record the detailed characteristics of purchasers, such as income and employment, the location and retail store where products were purchased, and product-level information such as product unit and size. This information is valuable for addressing other potential identification concerns related to the change in the purchasers' income and employment, the housing price, local conditions, and the retailers' behavior.

I integrate the prices and quantities of each product with its producer by using the GS1 US Data Hub.

7. Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

8. The ten demographic variables are household size, household income, head of household age, race, Hispanic origin, male head education, female head education, head of household occupation, the presence of children, and the Nielsen county size.

GS1 is the company that issues barcodes to producers.⁹ Their data record the company name and address for each barcode-level product, which provides a way to link barcode-level product information with its producer information. A “firm” in the database is defined based on the entity that purchased the barcodes from the GS1. Thus, a firm in the data could be a manufacturer, such as a Coca-Cola manufacturer that needs a barcode to sell its cherry-flavored 500-ml diet coke, or it could be a small retailer that wants to sell its private-label products. In the final sample, manufacturers account for approximately 62% of total sales, retailers account for approximately 33% of total sales, and other entities, such as wholesalers, account for less than 5% of total sales before the Lehman failure.

To collect producer information, I further combine the ACNielsen-GS1 matched database with the Orbis and Fixed Income Securities Database (FISD). Orbis is the firm-level dataset compiled by Bureau van Dijk (BvD) and has detailed administrative, financial, production and ownership information for both public and private firms. The dataset records the firms’ inventory and cash holdings, which are particularly helpful in testing the “fire sale” of inventory hypothesis. It also includes information such as the detailed four-digit NAICS industry codes, the number of foreign subsidiaries and branches, total assets, and the number of employees, which allow me to conduct additional empirical analyses and robustness checks. Similar to the Nielsen dataset, the data cover the period from 2004 to 2011; the dataset was downloaded from the BvD proprietary online browser for Orbis data.¹⁰ The online platform of the Orbis database provides software that automatically matches firms based on their name, address, industry code, and other information available in both the Orbis data and other data. I exploit this feature to merge the GS1 data and the corresponding barcode-level information with all other firm-level and bank-level information, including the FISD.¹¹ The FISD records historical corporate bond issuance and ratings and is used to extract information on the producers’ bond market access.

Finally, to extract information on bank lending to each producer, I include the Dealscan database. The Dealscan database contains comprehensive historical information on loan pricing and contract details, terms, and conditions. It mainly includes information on the syndicated loan market, in which more than one bank arranges a loan to a firm. The process usually begins with one or more lead arrangers signing a preliminary loan contract called a “mandate,” and these arrangers retain part of the loans and raise the rest of the funds from the participants. For each loan (or facility/package), the data include information on its purpose (e.g., corporate purposes or debt repayment), type (e.g., term loan or revolving line of credit), amount, interest spread, maturity, and lender information, which identifies the lead arranger and the lender’s contribution to each loan. In constructing the credit supply shock, I used loans identified as serving a corporate purpose or serving as working capital. *Carey and Hrycay (1999)* show that the data record between one-half and

9. GS1 provides a business with up to 10 barcodes for a \$250 initial membership fee and a \$50 annual fee. There are significant discounts on the cost per barcode for the firms that purchase larger quantities of barcodes (see <http://www.gs1us.org/get-started/im-new-to-gs1-us>).

10. The Orbis data used in the main analysis were downloaded in 2014. Downloading at this time maximizes the number of years that can be used alongside the Nielsen dataset because of how BvD manages the Orbis database. First, only the most recent ten years of the sample are available on the online platform. If I had downloaded data in 2015, then I would have missed the firm-level information for 2004. Second, there is a reporting lag of two years in the database (*Kalemli-Ozcan et al. 2015*). If I had downloaded data in 2013, then the coverage of 2011 (and 2012) would likely be incomplete.

11. I also hand-checked the validity of the merged sample.

three-fourths of the volume of outstanding commercial and industrial loans in the United States, and [Chava and Roberts \(2008\)](#) discuss that the coverage of Dealscan data increased from 1995 onwards.¹²

I supplement the combined data with Zillow housing price data and Current Population Survey (CPS) data on homeownership to specifically address the drop in housing prices and homeownership during this period. Additionally, I merged several bank-level variables used by [Chodorow-Reich \(2014\)](#) that reflect a change in bank health at the time of Lehman failure, demand elasticities from [Hottman, Redding, and Weinstein \(2016\)](#), industry-level inventory information from the NBER-CES database ([Bartelsman, Becker, and Gray 2000](#)), and an industry-level external financial dependence index ([Rajan and Zingales 1998](#)) measured by using firm-level cash and expenditure information from the Compustat database.

Table I reports the summary statistics of the combined sample. The merged dataset includes approximately 200 firms identified from the Orbis firm classification (BvD identification number) that were active in the syndicated loan market and that sold their products. See Online Appendix S4 for further details about the data used in this article. I dropped all firms that entered or exited after the Lehman failure to abstract away from firm dynamics. The median firm in the sample sells 30 products (UPCs) in approximately three product groups, such as pet food and school supplies. These 200 firms are relatively large compared to other firms in the consumer packaged goods market, where most firms are extremely small.¹³ Although this discrepancy raises concerns about the representativeness of the sample, the effect is likely to be at most underestimated, given that small firms are more sensitive than large firms concerning a credit supply shock. In addition, there remains a large degree of heterogeneity across firms and groups in the sample. The largest firm-group pair sells 130 times more UPCs than the median firm-group pair in the sample, and only approximately one-third of the firms in the sample are publicly listed or issued bonds before the Lehman failure. I exploit this variation to confirm that the effect of the credit supply shocks is larger for small firms. Additionally, I confirm my findings by using various sample weights in the regression analysis and by conducting an external validity check with more representative data.

A potential concern of using the combined database is that the information on prices and quantities is collected from households, whereas the credit supply shock, inventory, and liquidity are measured at the firm-level. Thus, the manufacturers' prices and sales information in the data might reflect the decision of retailers (or wholesalers) that purchase products from manufacturers and sell to households instead of the decision of the manufacturers that face the negative supply shock. To extract the adequate firm-level prices and quantities from the data, I follow [Hottman, Redding, and Weinstein \(2016\)](#) and aggregate the variables across retailers within firms. Given that a large fraction of manufacturers deal with a large number of retailers in the data, the idiosyncratic behaviors of retailers are likely to disappear for many manufacturers at the firm

12. If I use the 2004-2011 sample, then the share of loans covered in Dealscan relative to the total C& I loans is approximately 77%. This number should be interpreted with caution due to the discrepancy between the two databases, such as the unit of measure (e.g., flow vs. stock) and coverage (e.g., regulated banks vs. non-regulated banks). See [Ivashina and Scharfstein \(2010\)](#) for a more detailed discussion of the coverage of the Dealscan data during the financial crisis.

13. My sample considers approximately one-fifth of the sales and one-fourth of the total number of purchases in the Nielsen data. Originally, there were slightly less than 15,000 firms in the Orbis database integrated with the ACNielsen Homescan Panel, and most of these firms are dropped when I require that firms in the sample be active in the syndicated loan market before and after the Lehman failure. Most of these dropped samples do not have valid firm-level information, such as employment or total assets, in the Orbis data. It is likely that Orbis could not record the balance-sheet information for these exceptionally small firms. See Online Appendix S4.B.

TABLE I
SUMMARY STATISTICS FOR THE PRE-LEHMAN PERIOD (2006Q4-2007Q2)

variable	N	mean	sd	p10	p50	p90
Panel A: Firm-group variables						
\tilde{P}_{fg}	2055	3.90	5.92	1.21	2.47	6.80
Sales (in millions \$)	2055	28.51	110.34	0.04	1.36	56.08
Market share (in percent)	2055	4.84	12.59	0.01	0.37	14.40
Average # of UPCs per quarter	2055	31.43	76.01	1	10	72.33
Average # of buyers per quarter (in millions)	2055	2.33	9.11	0.00	0.12	4.76
Panel B: Firm variables						
ΔL_f	200	0.47	0.18	0.26	0.45	0.69
Lehman exposure	198	0.84	0.36	0.50	0.74	1.28
ABX exposure	198	1.06	0.28	0.81	1.01	1.34
Bank items	198	44.90	12.99	28.17	46.63	58.46
Bond issuance (binary)	200	0.28	0.45	0	0	1
Listed status (binary)	200	0.36	0.48	0	0	1
Firm age	198	47.82	35.87	13	35	97
Median spread (bp)	187	150.77	106.34	25	150	300
Average maturity (month)	197	53.65	15.21	32.5	60.0	61.0
Number of groups	200	10.28	19.28	1	3	26
Panel C: Group variables						
Demand elasticities across UPCs	100	8.13	4.25	5.02	6.93	14.06
Demand elasticities across firms	100	4.45	2.04	2.62	3.92	7.33
Number of firms	100	20.55	7.74	10.5	20.5	31.0

Note. The sample includes U.S. producers that sold products to households and loans obtained from banks before and after the Lehman failure and for which the purpose was classified as corporate use or as working capital. All the summary statistics are based on the pre-Lehman period, 2005:Q4 to 2006:Q2 and 2006:Q4 to 2007:Q2. \tilde{P}_{fg} , the firm-group-specific price index, is defined in Section II.C Market share is the sales share of firm f in group g . ΔL_f is the main measure of bank shock constructed from the change in loans issued by the bank, as described in Section II.B Lehman exposure is the percentage of the bank's syndication portfolio in which Lehman Brothers had a lead role in the loan deal. The ABX exposure variable equals the loading of the banks' stock return on the ABX AAA 2006-H1 index between October 2007 and December 2007. The Bank items variable is the sum of bank deposits and net trading revenue divided by total assets. All three measures are defined and discussed in Section II.B The demand elasticities are defined based on the nested CES demand system in [Hottman, Redding, and Weinstein \(2016\)](#), as discussed in the [Appendix](#).

level.¹⁴ In addition, even if there are retailers (or wholesalers) that are large enough to affect the aggregated firm-level manufacturer prices, according to the previous papers that study the incomplete pass-through (e.g., [Burstein and Gopinath 2014](#)), such effect would at most *underestimate* the main finding. I discuss this point in detail and conduct three additional empirical analyses, such as collecting and using the prices measured at the manufacturer level and using only retailers in the sample, which confirms the robustness of the main findings in Online Appendix [S6.B](#).

II.B Credit Supply Shock

I follow [Chodorow-Reich \(2014\)](#) to construct ΔL_f , a credit supply shock measure, which simply and coherently extracts the information on changes in the firms' access to credit as a consequence of a change in bank health.

I choose two periods, pre- and post-Lehman, to measure the credit supply shock to exploit the Lehman failure, which is known to be surprising and dramatic. The post-Lehman period comprises the three quarters immediately after the Lehman failure: 2008:Q4 to 2009:Q2. During this time, the TED spread, the measure of perceived credit risk, increased dramatically (Figure [Ia](#)). At the same time, the number of loans and loan amounts issued plummeted, and the interest spread spiked (Figure [Ib](#), [Ic](#)). The pre-Lehman period corresponds to the same three quarters in the earlier years, at the time of the credit market expansion: 2005:Q4 to 2006:Q2 and 2006:Q4 to 2007:Q2. These quarters were chosen to minimize seasonality concerns. To compare the extreme periods, I did not use the period immediately before the Lehman failure (2007:Q4 to 2008:Q2) for my main regression analysis.¹⁵ However, additionally defining this period as a pre-Lehman period does not alter the result, as shown in Online Appendix [S6.A](#). In fact, given the modest degree of financial market stress, this period is useful for a placebo test on the validity of the measure of Lehman exposure. In Online Appendix [S6.A](#), I show that the Lehman shock did not affect prices during this period.

Based on this timing, I construct the measure of bank shock as follows. Given the change in bank health measures, I take a weighted average of bank health for each firm to generate the firm-specific credit supply shock:

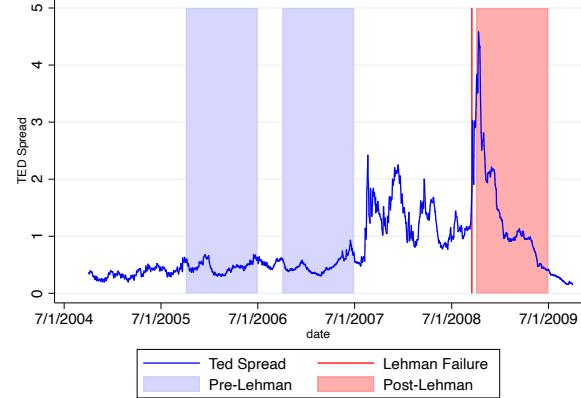
$$(1) \quad \Delta L_f = \sum_{b \in S_f} \alpha_{fb,\text{last}} \Delta(\text{Bank Health})_{-f,b}$$

where $\Delta(\text{Bank Health})_{-f,b}$ is a measure of the firm-bank-specific change in bank health defined in equation [\(2\)](#), and weight $\alpha_{fb,\text{last}}$ is the bank b 's share of the total amount of the last syndicated loan it made to firm f before the Lehman failure.¹⁶ S_f denotes the set of banks that lend to firm f for the last syndicated loan that

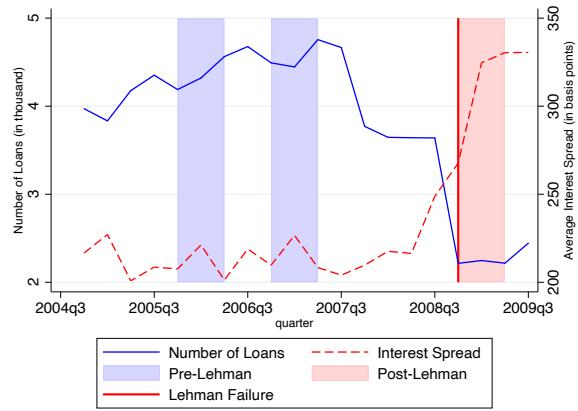
14. There are 187 retailers per firm on average during the pre-Lehman period in the final sample.

15. Total commercial and industrial (C&I) loans also did not fall in this period. However, this is due to an increase in credit drawdowns by corporate borrowers on existing credit lines, not the issuance of new loans ([Ivashina and Scharfstein 2010](#)).

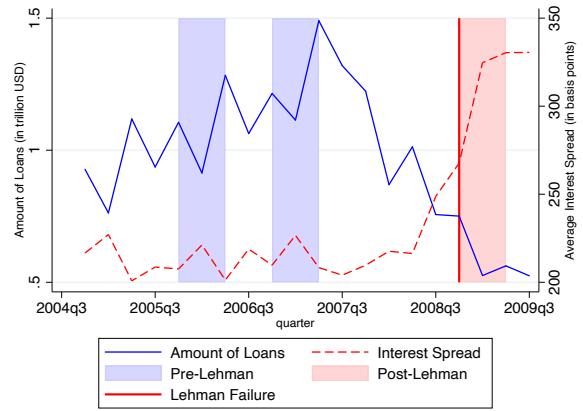
16. The weight reflects the fact that multiple banks arrange a loan to a firm and that different banks lend different amounts for a particular loan. The Dealscan database reports only approximately one-third of α_{jbt} among total loans. I impute the missing α_{jbt} by using the method in [Chodorow-Reich \(2014\)](#).



(a) TED SPREAD



(b) NUMBER OF LOANS AND INTEREST SPREAD



(c) AMOUNT OF LOANS AND INTEREST SPREAD

FIGURE I

TIMING OF THE CREDIT SUPPLY SHOCK (ΔL_f)

Note. (a) plots the TED spread, (b) plots the total number of loans and the average interest spread, and (c) plots the total amount of loans and the average interest spread. The pre-Lehman period includes the following six quarters: 2005:Q4 to 2006:Q2 and 2006:Q4 to 2007:Q2. The post-Lehman period includes the following three-quarters: 2008:Q4 to 2009:Q2. The TED spread, which measures the perceived credit risk, is defined as the difference between the three-month T-bill and the interbank borrowing rate. The number (amount) of loans is the total number (amount) of loans issued according to the Dealscan database, and the interest spread is the amount that the borrower pays in basis points over LIBOR for each dollar drawn down and is averaged across loans within each quarter. The Lehman failure occurred in September 2008 at the end of 2008:Q3.

firm f borrowed before the Lehman failure. For example, consider the J.M. Smucker Company, which is famous for its fruit spreads and peanut butter. Suppose that it borrowed from two banks—Chase Bank and Citibank—for its last loans before the Lehman failure and that 80% of its loans were borrowed from Chase Bank and 20% were borrowed from Citibank. Then, I used 0.8 and 0.2 as the weights to take a weighted average of the changes in bank health for Chase Bank and Citibank, respectively, to measure the credit supply shock faced by Smucker's. Although I used the last loan share as a weight to maximize the effect of the bank shock on firms, using the average loan share of the whole pre-Lehman period does not alter the results, as shown in Online Appendix S6.F. This finding is likely attributable to the stable firm-bank relationship.

The $\Delta(\text{Bank Health})_{-f,b}$ is given by the following expression:

$$(2) \quad \Delta(\text{Bank Health})_{-f,b} = \frac{\sum_{j \neq f} \alpha_{jb,\text{post}} \times \mathbb{1}(\text{b lent to j in post-Lehman})}{\frac{1}{2} \sum_{j \neq f} \alpha_{jb,\text{pre}} \times \mathbb{1}(\text{b lent to j in pre-Lehman})}$$

where $\mathbb{1}()$ is an indicator variable equal to 1 if what is in parentheses is true and is 0 otherwise; α_{jbt} denotes bank b 's share of the total amount of the loan for each syndicated loan that it made to firm j in period t . I divide the denominator by 2 to balance the periods as the pre-Lehman period consists of six quarters, whereas the post-Lehman period consists of three quarters.

Roughly, equation (2) is a change in the number of loans issued by banks: the number of loans made by bank b in the post-Lehman period over the number of loans made by bank b in the pre-Lehman period. There are two additional complications. First, to reflect the importance of each loan issued by bank b , I multiply the weight α_{jbt} for each loan made by bank b to firm j . Second, I intentionally omit firm f from the summation to generate the firm- f -bank- b -specific change in bank health. This “leave-one-out” method partially eases concerns related to the credit demand channel. For example, consider again the example of Chase Bank, which lends to Smucker's and other companies. If I use Chase Bank's loan to Smucker's to measure Chase's change in bank health, then this measure might reflect the change in credit demand that arise from Smucker's product market decisions or financing policies rather than from the change in Chase's willingness to supply credit to Smucker's. To address this concern, in constructing Smucker's credit supply shock, I examine Chase's lending to all firms excluding Smucker's, for both the pre- and post-Lehman periods. I do the same to measure the change in Citibank's bank health and then take a weighted average across Chase and Citibank to construct Smucker's credit supply shock, as shown in equation (1).¹⁷

To assess the validity of the credit supply shock measure, I check the sample balance and find no significant difference in firm characteristics across the credit supply shock. I first regress the pre-Lehman firm-level characteristics on the credit supply shock that I constructed. As shown in Table II, the credit supply shock is not correlated with the purchasers' characteristics¹⁸ or with the firms' access to the loan market,

17. Note that I use a number of loans instead of loan amounts. I do this to minimize the measurement error due to the imputation of α_{fbt} . However, using loan amounts does not change the results, as reported in Online Appendix S6.F. These results are likely because the drop in loans during this period is driven largely by a change in the number of loans rather than by the loan amounts. The loan size remained stable in this period (Darmouni 2020).

18. Housing price is available at the zip-code level from the Zillow database, homeownership is available at the county-level from the census, and income, employment, education, and household size are available from Homescan Panel data. For each measure, I

listed status, bond market access, age, size, or loan characteristics. These results suggest that the measure of credit supply shock constructed for this period reflects the change in bank health rather than borrower or purchaser characteristics. Additionally, I implement a test introduced in [Khwaja and Mian \(2008\)](#) and conducted in [Chodorow-Reich \(2014\)](#) to check for the selection in the unobserved firm characteristics in my sample. Consistent with [Chodorow-Reich \(2014\)](#), I find that the unobserved firm characteristics are balanced. The details of this analysis are reported in Online Appendix [S6.I](#).

TABLE II
COMPARISON OF PRE-LEHMAN OBSERVED CHARACTERISTICS

	(1) ln(housing price) Log	(2) Home ownership %	(3) ln(income) Log	(4) Employment %	(5) Education Years	(6) Household size Number
Unit						
ΔL_f	-0.03 (0.02)	0.00 (0.00)	-0.00 (0.02)	0.00 (0.01)	-0.03 (0.05)	0.02 (0.03)
R^2	0.01	0.01	0.00	0.00	0.00	0.00
obs	202	202	202	202	202	202
Unit	Number of loans Number	Amount of loans \$b	Bond D	List D	Age Years	Multi-lead D
ΔL_f	0.93 (1.16)	2.12 (2.33)	-0.08 (0.06)	-0.06 (0.07)	2.07 (5.53)	-0.02 (0.04)
R^2	0.00	0.00	0.01	0.00	0.00	0.00
obs	206	206	206	206	204	206
Unit	Spread (median) bp	Maturity Month	Total assets \$m	Employment k	Inventory/asset %	Cash/asset %
ΔL_f	-14.95 (23.87)	1.61 (2.40)	7.14 (7.49)	73.00 (63.16)	-0.00 (0.03)	-0.02 (0.02)
R^2	0.00	0.00	0.03	0.03	0.00	0.01
obs	191	203	121	109	72	73

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are heteroskedasticity-consistent. For the variable units, \$b is billions of dollars, \$m is millions of dollars, D is a dummy, k is one thousand, and bp is basis points. ln(housing price), Home ownership, ln(income), Employment, Education, and Household size are the household characteristics measured at the firm-group-level. Total assets and employment are firm-level variables in Orbis and are averaged across 2004, 2005, and 2006. The number and the amount of loans are total sums, multi-lead and maturity are averages, and the spread is a median across loans within the pre-Lehman period. Bond access is equal to 1 if the companies issue bonds in 2004:Q3 to 2007:Q2 and is 0 otherwise.

In addition to the measure of credit supply shock constructed above, to confirm the findings, I use three bank-level measures of the change in bank health as instrumental variables. The three measures are (i) the banks' exposure to Lehman, (ii) the banks' exposure to asset-backed securities (ABX), and (iii) bank statement items that are unlikely to be correlated with borrower characteristics. Lehman exposure is the fraction of a bank's syndication portfolio in which Lehman Brothers had a lead role. This measure relies on the notion that certain banks dealt more with Lehman Brothers than other banks and decreased their lending relatively more than other banks decreased their lending after the Lehman collapse. According to [Ivashina](#)

first take a weighted average across households (or zip-code or country) within firms and groups by using the sample weight; then I further take a sales-weighted average across groups within each firm to construct the measures reported here.

and Scharfstein (2010), this pattern occurs because the borrowers that had a credit line in which Lehman Brothers had a lead role aggressively drew down as a precautionary motive when the lead lender became bankrupt, which drained the liquidity of other lenders that dealt closely with Lehman. The bank's exposure to asset-backed securities is the correlation between its daily stock return with the return on the ABX AAA 2006-H1 index. This index generates variation in the changes in bank health due to the banks' exposure to the toxic residential mortgage-backed securities issued during the second half of 2005. Finally, the bank statement items variable is the sum of a bank's net trading revenue—where many subprime write-downs occurred—and bank deposits divided by its assets before the Lehman failure. For reasons that are plausibly orthogonal to a borrower's pricing decision, all three measures are likely to generate variation in a change in bank health.¹⁹ For each bank-specific change in a bank health measure, I construct a firm-level credit supply shock by following equation (1). The correlations among these three variables are weak at the firm level in my sample, which generates a presumably independent variation in the producer's credit supply condition.²⁰

II.C Firm-Group Price Index

This paper adopts the nested CES utility function in Hottman, Redding, and Weinstein (2016) to build the firm-group-specific price index from the ACNielsen Homescan Panel database.²¹ The utility-based price index has two main advantages over other indexes; the index is consistent with the standard models that use the CES utility function including the model discussed in Section VI, and it incorporates the effect of product quality and variety changes on output prices. In particular, the index can be exactly decomposed into the conventional price index and the quality-variety correction and allows me to quantify the effect of the credit supply shock on prices through quality and variety changes. Although previous studies generally identified the importance of such quality and variety changes in explaining output price dynamics (Nakamura and Steinsson 2012; Hottman, Redding, and Weinstein 2016), the effect of the credit supply shock on the quality-variety margin of the output price index is negligible as shown in Online Appendix S2.A. This result is largely consistent with the hypothesis proposed in this paper. If the firms that face a negative credit supply shock liquidate inventory and decrease price to generate extra revenues from the product market, then it is not obvious why they would change their product quality or variety to adjust their output prices.²²

Given that the quality-variety margin does not make much difference in the main results, in this section, for readability, I present the simple conventional price index that subtracts the quality-variety correction from the utility-based price index. The Appendix presents the nested-CES demand system with the derivation of the utility-based price index. Although all the tables in the main body of the paper are presented by using the conventional price indexes, the results are robust to using the utility-based price index. Using other conventional price indexes, such as the Laspeyres, Paasche, and the Tornqvist price index, does not change

19. I am grateful to Gabriel Chodorow-Reich for making these measures available on his website.

20. $\text{Corr}(\text{Lehman, ABX})=0.04$, $\text{Corr}(\text{ABX, BankItem})=0.06$, $\text{Corr}(\text{Lehman, BankItem})=0.44$

21. This framework is isomorphic to the nested logit demand system in which heterogeneous consumers demand a single product in each stage (Anderson, de Palma, and Thisse 1992) and is more flexible than the standard CES utility function (Atkeson and Burstein 2008; Edmond, Midrigan, and Xu 2015).

22. However, the credit supply shock influences the market share through the quality adjustment. See Online Appendix S2.B.

the results, as shown in Online Appendix [S6.G](#).

The conventional price index is a simple geometric average of prices across UPCs within the firm, product group, and time (quarter):

$$(3) \quad \tilde{P}_{fgt} = \left(\prod_{u \in \Omega_{fgt}} P_{ut} \right)^{1/N_{fgt}}$$

where subscript u is the UPC or barcode-level product, f is the firm, g is the product group, and t is time. Ω_{fgt} is the set of the UPCs made by firm f in product group g at time t , and N_{fgt} is the number of UPCs made by firm f in product group g at time t . P_{ut} is the price of the UPC at time t and is measured by dividing the total sales by quantities at the UPC-time-level. Note that the aggregate price index measured from this geometric average price index follows the official BLS price index closely, as shown in Online Appendix [S3.A](#). Adding the quality-variety correction term to this geometric average price index recovers the utility-based price index.

III THE EFFECT OF THE CREDIT CRUNCH ON THE OUTPUT PRICE

In three complementary ways, this section presents the effect of a credit supply shock on producers' output price dynamics. First, I visualize the effect by plotting the aggregate price indexes of two groups of firms that face different degrees of credit supply shocks. Second, I confirm the visualization by conducting more rigorous regression analyses with the continuous measure of a credit supply shock, three other instruments, and a rich set of control variables. Finally, I draw an event study plot to show the dynamic effect of the credit supply shock.

To visualize the effect, I divide my sample into two categories based on the measure of the credit supply shock (ΔL_f) defined in equation [\(1\)](#). One category of firms faces a negative credit supply shock larger than the 80th percentile of the shock's size distribution, and the other category of firms faces the negative credit supply shock smaller than the 20th percentile of its distribution.²³

For each category of firms, I measure the price index by taking a geometric average of the firm-group-time-level price index (\tilde{P}_{fgt}) defined in equation [\(3\)](#) across firms within product group and time:

$$(4) \quad \tilde{P}_{gt,c} = \left(\prod_{f \in \Omega_{gt,c}} \tilde{P}_{fgt} \right)^{1/N_{gt,c}}$$

where $\Omega_{gt,c}$ is the set of the firms in product group g and category c at time t , and $N_{gt,c}$ is the number of firms in product group g and category c at time t . Similar to the firm-group-level price index, this product group-level price index is the part of the nested-CES utility-based price index that does not adjust for a variety-quality correction. I aggregate this index across product groups within category and time by using the

23. Setting different thresholds, such as the 75th and the 25th percentile of the distribution, yields similar results.

following Tornqvist price index:

$$(5) \quad \frac{\tilde{P}_{t,c}}{\tilde{P}_{t_0,c}} = \prod_{g \in \Omega_{t,c}} \left(\frac{\tilde{P}_{gt,c}}{\tilde{P}_{gt_0,c}} \right)^{(\varphi_{gt,c} + \varphi_{gt_0,c})/2}$$

where $\Omega_{t,c}$ is the set of the product groups g in category c at time t . t_0 is the base time (2004:Q1) and $\varphi_{gt,c}$ is a market share of product group g at time t in each category. The same procedure is used to compare the scanner price index made from Nielsen data with the BLS official price index in Online Appendix [S3.A](#).

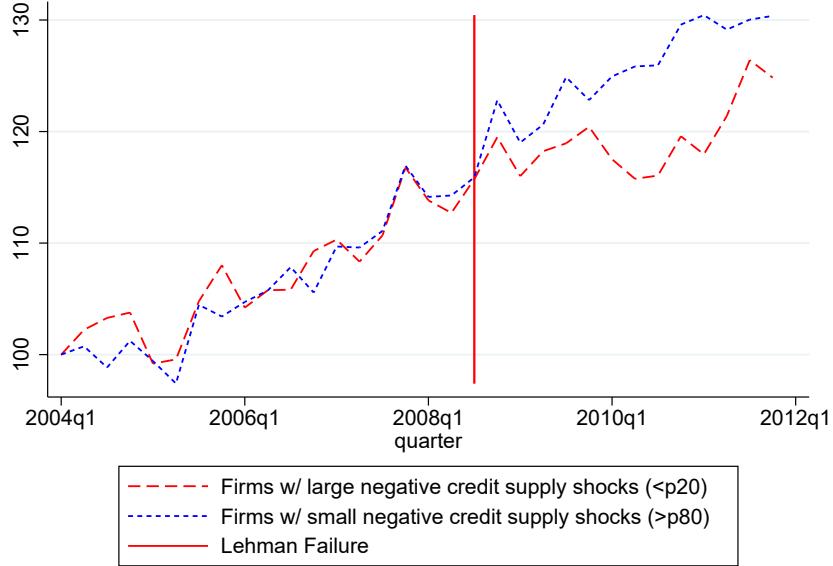


FIGURE II
DIFFERENTIAL CHANGE IN PRICE INDEXES

Note. The differential change in the price index between credit-constrained firms and their unaffected counterparts. The red dashed line denotes the quarter-level price index of the firms that face a large negative credit supply shock, and the blue dotted line denotes the quarter-level price index of the firms that face a small negative credit supply shock. The vertical solid red line shows the timing of the Lehman failure, which is used to measure the credit supply shock, as shown in Section [II.B](#).

Figure II plots the price index measured in equation (5). Although the category-specific measure of the price index does not fully utilize the credit supply shock variation across firms, the figure clearly illustrates the main empirical results in this paper. The two price indexes, which are made by using two different categories of firms, follow each other closely before the shock realizes. This empirical pattern reflects that pricing behaviors are similar across the firms that face different degrees of a credit supply shock in the pre-shock period. However, after the shock realizes, the price index of the firms that face a larger negative credit supply shock decreases relative to the price index of their counterparts. The gap between these two indexes persists for several quarters after the shock happens but eventually closes at the end, which shows that the effect is temporary. In addition, this figure makes it clear that the micro-level empirical analyses in this paper study

the relative changes in prices and are not vulnerable to aggregate shocks, such as the aggregate demand changes in this period.

To confirm the visualization, I more rigorously examine the effect of a credit supply shock on producers' output price dynamics by using the following specification:

$$(6) \quad \Delta \ln \tilde{P}_{fg} = \lambda_g + \beta (-\Delta L_f) + \theta X_f + \varepsilon_{fg}$$

where subscript f is the firm and g is the product group. \tilde{P}_{fg} is the firm-group-specific price index that I constructed from the ACNielsen barcode-level data discussed in Section II.C. In measuring \tilde{P}_{fg} , to make the price index comparable to the credit supply shock, I take the geometric average of \tilde{P}_{fgt} in equation (3) across quarters within 2006:Q4-2007:Q2 (the last three quarters in the pre-Lehman period) and 2008:Q4-2009:Q2 (the post-Lehman period).

Then, I take the difference of the logged price index across the pre- and post-Lehman periods. ΔL_f measures the change in the firm-level credit supply as a result of the deterioration of bank health, as discussed in Section II.B. I change the sign of ΔL_f to interpret β as a result of a *negative* credit supply shock on output prices. X_f includes the initial and lagged firm-level control variables. λ_g is allowed in the regression to compare product prices *within* product groups. I weighted the regression by the initial total sales in each product group and firm to reveal the aggregate dynamics, similar to the analysis in Amiti and Weinstein (2018). Using different regression weights, such as the number of products that makes the estimated regression coefficient match the product-level regression coefficient, does not change the results, as shown in Online Appendix S6.E. β is the coefficient of interest that measures the effect of a credit supply shock on the change in output prices.

The key identification assumption to make a causal interpretation of β is that any confounding factors that affect a firm's pricing decisions do not simultaneously affect its lender's lending to other firms. Concerning this assumption, the biggest identification threat is that the demand shock can potentially affect both the firms' pricing decisions and their previous lenders' lending decisions toward other borrowers. For example, the large drop in housing prices in this period affected different consumers differentially (Mian, Rao, and Sufi 2013). Thus, across the products made by different firms, these consumers may purchase products differentially, and, in turn, these firms could differentially demand from their lenders a different number of loans. If these firms are large enough for the lender to cut its lending to other borrowers, then my assumption is violated.

I argue that the key assumption in this article is well supported. The narrative evidence suggests that bank health deterioration in this period originated from the Lehman failure (Ivashina and Scharfstein 2010), real estate and toxic assets (Santos 2011), and the bank liability structure (Fahlenbrach, Prilmeier, and Stulz 2012) rather than from the corporate loan sector. The fact that the corporate loan sector did not cause the credit market disruption in this period is particularly true for the consumer packaged goods market used in the sample; relative to consumers in other sectors, these consumers did not change their purchasing behavior dramatically. The empirical pattern of the aggregate price and quantity of loans during this period supports

this view. After the Lehman bankruptcy, there was not only a dramatic drop in the number and amount of loans but also a sudden large increase in the interest spread (Figure [Ib](#), [Ic](#)). This credit market behavior suggests that there was a shift in credit supply rather than in credit demand, at least at the aggregate level.

Additionally, I allow a rich set of initial and lagged firm-level characteristics (X_f) in this regression to address potential spurious correlations. To control for firms' liquidity substitution from loan markets to bond markets when banks cannot provide a loan ([Becker and Ivashina 2014](#)), I include a pre-Lehman bond rating and the bond issuance information for each firm. The fixed effects of the firms' four-digit NAICS industry, listed status, and a firm size indicator are included to compare firms within these categories. To address the differential degree of loan market access for each firm, I control for the number and amount of loans that firms received in the pre-Lehman period and for the number of loans that matured in the post-Lehman period because firms would suffer more if they had to pay out their loans in the post-Lehman period ([Almeida et al. 2012](#)). Furthermore, to make a reliable comparison across firms, I control for the firm age, the type of the last loan (term loan vs. revolver/line), the year that the last loan was issued, whether a firm dealt with multiple lead banks, and the last loan's interest spread and maturity. I also add a lagged change in the output price index to control for the potential pre-trend. In addition, Nielsen data provide detailed purchaser characteristics, such as income, education, employment, age, and household size. I further merge the data with housing price data at the zip code level from the Zillow data and homeownership at the country level from the census data. Adding these purchasers' characteristics does not change the results, as shown in Online Appendix [S6.C](#). Note that the observed pre-Lehman borrower and purchaser characteristics are balanced, as shown in Table [II](#).

Moreover, to confirm my findings, I use the following three instruments that are not highly correlated but that generate plausibly exogenous variations in the firms' credit supply conditions: Lehman exposure; ABX securities exposure; and bank statement items. These measures are used as instrumental variables to consistently interpret the coefficients. Using the cross-sectional variation in Lehman exposure is the well-established identification strategy used in the literature to study bank, fund, and firm behavior (e.g. [Ivashina and Scharfstein 2010](#); [Aragon and Strahan 2012](#); [Chodorow-Reich 2014](#); [Darmouni 2020](#)). Before its failure, Lehman was the fourth-largest investment bank and had more than \$600 billion in assets, and its collapse was surprising and dramatic. By using this instrument, I effectively assume that what happened to companies such as Smucker's in the consumer packaged goods market did not lead Lehman to bankruptcy. This assumption is very persuasive, given the ample evidence that the Lehman failure was due to the bank's risky lending, investment strategy, and toxic mortgage-backed securities holdings. Using ABX exposure or bank statement items (the sum of bank deposits and net trading revenue to assets) also generates a credit-supply variation that is plausibly uncorrelated with the factors that affect companies' pricing decisions. The first-stage regression result for each of the three instruments is reported in Table [III](#). All the estimated coefficients are intuitive and statistically significant.

In Online Appendix [S6](#), I additionally conduct numerous robustness checks regarding concerns such as product quality and variety, retailers' decisions, local conditions, purchaser behavior, foreign exposure, initial cash holdings, pre-trends, and external validity. In particular, I utilize the quantity information available

TABLE III
FIRST-STAGE REGRESSION

	(1)	(2)	(3)
	ΔL_f		
Lehman exposure	-0.359*** (0.088)		
ABX exposure		-0.262*** (0.093)	
Bank items			0.422*** (0.108)
Firm-level controls	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes
$E[\Delta L: IV_{p90}-IV_{p10}]$	-.247	-.361	.479
Observations	1658	1658	1658

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, and the regression is weighted by initial sales. The firm-level controls are the firm's listed status, four-digit NAICS FE, age, size, bond rating, number of loans, amount of loans, loan type, loan-year FE, multi-lead FE, number of loans due in the post-Lehman FE, loan spread, loan maturity, and lagged $\Delta \ln P_{fg}$

in the Nielsen data and find that the firms that face a negative credit supply shock increase their market share. If the negative credit supply shock measures the negative demand shock, the firms that face this shock would experience a decrease in market share rather than an increase in market share. I show this result and rationalize it with the inventory adjustment hypothesis in Section IV.A

The other assumption of the regression analysis is the long-term firm-bank relationship or the existence of switching costs when companies must form new relationships with banks. If companies can quickly change to other banks when their previous lenders cannot issue loans, these companies might not be affected by bank shock. However, it is very unlikely that firms can easily find a new lender quickly because of the adverse selection for switchers that prevents lenders from providing new loans. Additionally, the monitoring cost is likely to decline more for repeated borrowers, which also eases the moral hazard problem for lenders. This relationship lending is especially true for the United States, where the Secretary of the Treasury has made KYC (Know Your Customer) mandatory for all U.S. banks since 2002. As a result of this regulation, there is a non-trivial implicit cost for U.S. banks in establishing new relationships with customers. In particular, I examine a credit market disruption period, during which banks are especially hesitant to form new relationships.²⁴

Table IV shows the empirical results based on equation (6). The first column reports the ordinary least squares regression results without conditioning on the control variables. The coefficient is negative

24. Empirically, Chodorow-Reich (2014) confirm this sticky firm-bank relationship with a regression analysis.

and statistically significant, which confirms what Figure II presents with more variation in the measure of the credit supply shock. The second column adds all the firm-level control variables, including the product group and NAICS 4-digit industry code fixed effects. Although adding the firm-level controls increases the estimated coefficient slightly, adding the fixed effects raises the effect substantially, which emphasizes the importance of comparing products in the same groups and comparing the firms that sell the same primary product industry code. Columns (3)-(6) present the instrumental variable regression results obtained by using Lehman exposure, ABX securities exposure, bank statement items, and all three variables together as instrumental variables. Regardless of whether OLS is used with the main credit supply shock variable or which instruments are used, the estimated coefficients are negative, statistically significant at the 5% level, and quantitatively similar.

TABLE IV
MAIN RESULTS

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \ln \tilde{P}_{fg}$: 2006q4-2007q2 to 2008q4-2009q2					
	OLS		(- ΔL_f) instrumented using			
(- ΔL_f)	-2.31*** (0.52)	-8.31*** (1.85)	-7.13** (3.13)	-7.36** (3.03)	-7.31** (3.42)	-7.25*** (1.97)
Firm-level controls	No	Yes	Yes	Yes	Yes	Yes
Product group FE	No	Yes	Yes	Yes	Yes	Yes
Four-digit NAICS FE	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			16.70	7.90	15.20	11.90
J-statistics p-value						1.00
$E[\Delta \ln \tilde{P}]$	11.4	11.4	11.4	11.4	11.4	11.4
$E[\Delta \ln \tilde{P}]:\Delta L_{p90}-\Delta L_{p10}$	-5	-18.1	-15.6	-16.1	-15.9	-15.8
Observations	1658	1658	1658	1658	1658	1658

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by firm and product group; the regression is weighted by initial sales; and firm-level controls are the firm's listed status, age, bond rating, number of loans, amount of loans, loan type, loan-year FE, multi-lead FE, number of loans due in the post-Lehman FE, loan spread, loan maturity, and lagged $\Delta \ln P_{fg}$

The regression results clearly show that the firms that face a negative credit supply shock decrease their output prices significantly relative to the output prices of their counterparts. I standardize the credit supply shock measure (ΔL_f) to interpret the coefficient. Conditioned on the control variables, a one-standard-deviation increase in the negative credit supply shock decreases output prices by approximately 8%. If I compare extremely credit-constrained firms and credit-unconstrained firms in the sample by looking at the 90th-10th percentile ratio, the effect is approximately 15 to 18 percentage points. In Online Appendix S6.J, I additionally confirm the empirical results by showing no pre-trends with the same regression specification and credit supply shock but with a change in the log price index in previous periods, from 2004:Q4-2005:Q2

to 2006:Q4-2007:Q2.

In addition to the main regression analysis, I conduct an event-study analysis based on the measure of Lehman exposure by using the following regression specification:

$$(7) \quad \ln P_{fg,t} - \ln P_{fg,t-4} = \lambda_{gt} + \beta_t(-\Delta L_f) + \theta X_{ft} + \varepsilon_{fgt}$$

where t is the quarter, not the pre- and post-Lehman periods. For this firm-quarter-level analysis, I use the full utility-based price index defined in the [Appendix](#) to minimize the measurement errors associated with product entry and exit. Rather than instrumenting the main measure, the measure of Lehman exposure is directly used in the regression as a reduced form.²⁵ Based on this regression analysis, I estimate the effect of a credit supply shock for all quarters in the data.

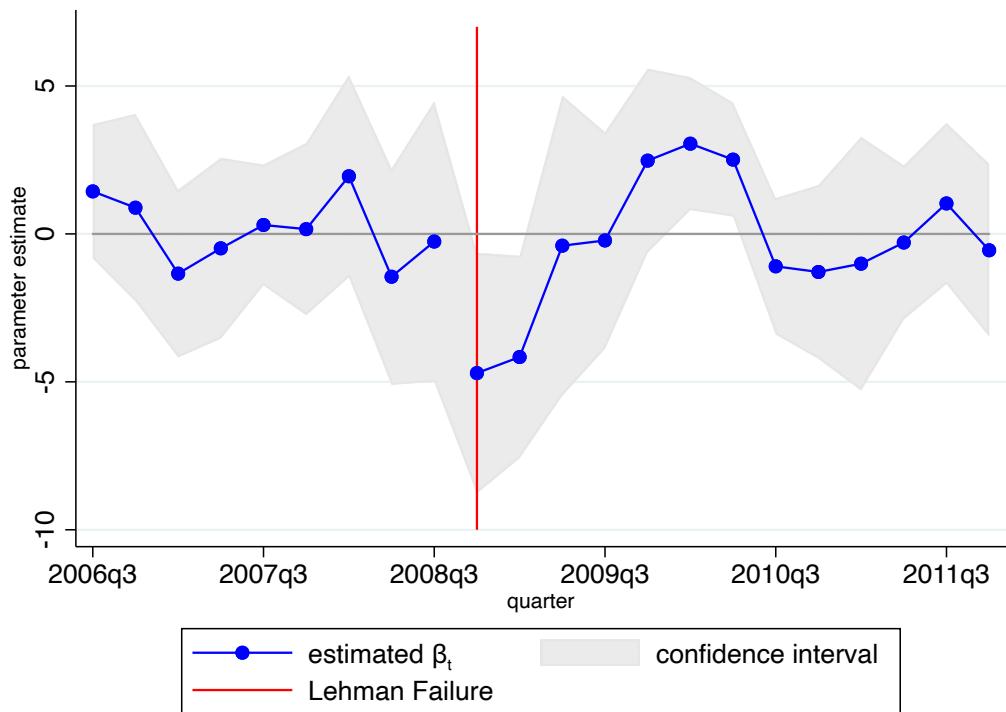


FIGURE III
PRICE DYNAMICS AND CREDIT MARKET DISRUPTIONS

Note. This figure is based on equation (7), and the measure of the Lehman exposure is directly used as a reduced form. The parameter estimates ($\hat{\beta}_t$) for each quarter are plotted. A 95% confidence interval is reported for each estimated coefficient, standard errors are clustered by firm and product group, and the regression is weighted by initial sales. The firm-level controls are the firm's listed status, 4-digit NAICS FE, age, bond rating, the number of loans, the amount of loans, the loan type, loan-year FE, multi-lead FE, the number of loans due in the post-Lehman FE, loan spread, and loan maturity.

The estimated coefficients are plotted in Figure III. The figure reveals the transparent dynamic effect of

25. Instrumenting the main credit supply shock with the Lehman exposure does not change the qualitative results.

the bank shock on output price dynamics. The estimated coefficients are not statistically different from 0 before the Lehman failure, which suggests that there is no pre-trend. However, at the time of the Lehman failure, the coefficients are negative for the first two quarters and near 0 for the subsequent quarters, which shows that the firms that faced a negative credit supply shock decreased their output prices. After a year, however, the estimated coefficients become positive for approximately three quarters and turn into 0 for the remaining quarters. This plot clarifies that the effect is temporary and that firms increase their output prices in the medium and long run. Note that both Figure II and Figure III show that the effect is temporary, but the duration of the effect is shorter in the latter figure. This is largely because the regression analysis used in Figure III allows more variation in the credit supply shock and has additional control variables, including fixed effects.

The fire sale inventory hypothesis is fully consistent with this temporary effect. If it is true that firms decrease their output prices by liquidating inventory and dumping their products on the market, then they would not be able to sell their inventories forever, and, thus, they must accumulate inventory at some point, which suggests that the effect should be temporary. I discuss this hypothesis in detail in the next section.

IV MECHANISM: FIRE SALE OF INVENTORY

IVA *Inventory, Market Share, Liquidity, and Employment*

The result in the previous section seems to be counterintuitive, as most studies interpret financial distress as an increase in credit cost and therefore predict an increase in output prices due to a negative credit supply shock.²⁶

I propose a hypothesis that can rationalize the empirical finding: I call it the fire sale of inventory hypothesis. When firms face a negative credit supply shock and cannot borrow from banks, they have an incentive to aggressively liquidate their inventories and sell their products at a low price to generate extra cash flow from the product market. From a corporate liquidity management perspective, the firms that cannot borrow from their lenders try to accumulate cash by selling off their inventory at low prices to generate extra cash flow.

Figure IV plots the total business inventory and corporate cash holdings to see whether this hypothesis is plausible. The aggregate inventory increased before the financial panic, but in the middle of the financial panic, it plummeted.²⁷ Aggregate corporate cash holding seems to be stable and does not correlate with the aggregate inventory before the financial panic, but amid the financial panic, it rises dramatically. Note that the period of financial panic when the total inventory fell and corporate cash holdings rose is precisely the time when the aggregate output price indexes decreased temporarily, as shown in Online Appendix S3. These

26. The papers that emphasize the effect of financial cost on output price include Barth and Ramey (2002), Del Negro, Giannoni, and Schorfheide (2015), and Christiano, Eichenbaum, and Trabandt (2015). Other mechanisms are discussed in the literature. For example, Gilchrist et al. (2017) places more emphasis on consumer habits, and Chevalier and Scharfstein (1996) emphasize both consumer habits and strategic interaction in explaining firms' price-setting behavior due to financial friction.

27. Using other measures of aggregate inventory, such as the real manufacturing and trade inventories or the aggregated measure of inventory from the Orbis database, shows a similar pattern.

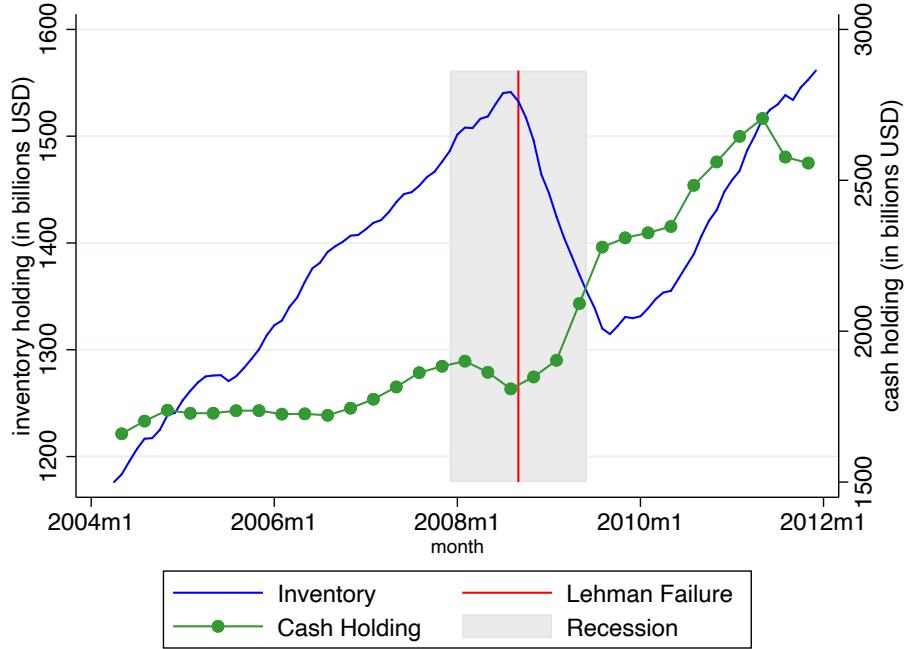


FIGURE IV
AGGREGATE INVENTORY AND CORPORATE CASH HOLDINGS

Note. This figure plots the total business inventory and corporate cash holdings. The aggregate inventory data are downloaded from the FRED Economic Data. The aggregate corporate cash holding is measured by using the quarterly Compustat database, which was downloaded from the WRDS. It is aggregated across firms within quarters after excluding financial firms and utilities and is seasonally adjusted by using the X-13ARIMA-SEATS Seasonal Adjustment Program from the census. More information on the Compustat data is given in Online Appendix S4.

movements in aggregate business inventory, corporate cash holdings, and output price indexes suggest that the proposed hypothesis is plausible, at least at the aggregate level.

To rigorously support the hypothesis, I return to the micro-level data and the corresponding identification strategy. Identical to equation (6), except for the dependent variable, the following regression specification is used:

$$(8) \quad \Delta Y_{fg} = \lambda_g + \gamma(-\Delta L_f) + \theta X_f + \varepsilon_{fg}$$

where ΔY_{fg} equals four different dependent variables, namely, a change in inventory, market share, cash holding, and employment.²⁸ Note that the market share is the only firm-group specific variable among the four dependent variables and that product-group fixed effects are not allowed in the regression for other

28. (1) Inventory_{fg}: $\frac{\text{Inv}_{f,2008} - \text{Inv}_{f,2006}}{\frac{1}{2}(\text{Inv}_{f,2006} + \text{Inv}_{f,2008})}$, (2) Market Share_{fg}: $\left(\frac{\text{sales}_{fg}}{\text{sales}_g} \right)_{2008q4-2009q2} - \left(\frac{\text{sales}_{fg}}{\text{sales}_g} \right)_{2006q4-2007q2}$, (3) Cash Holding_{fg}: $\left(\frac{\text{cash}}{\text{total asset}} \right)_{f,2008} - \left(\frac{\text{cash}}{\text{total asset}} \right)_{f,2006}$, (4) Employment_{fg}: $\frac{\text{Emp}_{f,2008} - \text{Emp}_{f,2006}}{\frac{1}{2}(\text{Emp}_{f,2006} + \text{Emp}_{f,2008})}$.

variables. ΔL_f is the credit supply shock constructed in Section II.B, and X_f is the vector of corresponding firm-level control variables.

I provide strong empirical support for the fire sale of inventory hypothesis, as shown in Table V.²⁹ Consistent with the hypothesis, I observe inventory holding at the firm-level and find that the firms that face a negative credit supply shock liquidate their inventories.³⁰ Such firms increase their market share, which suggests that these firms generate extra sales from the product market by selling off their inventory. Such firms accumulate more cash, which implies that they convert inventories (illiquid assets) to cash (liquid assets). These firms lay off workers, an action that is a well-known result in the literature.

TABLE V
FIRE SALE OF INVENTORY HYPOTHESIS: EMPIRICAL SUPPORTS

	(1)	(2)	(3)	(4)
Y_{fg}	Inventory $_f$	Market Share $_{fg}$	Cash Holding $_f$	Employment $_f$
($-\Delta L_f$)	-30.1** (13.4)	2.4** (1.2)	5.6*** (1.8)	-23.5** (10.9)
instrumented using Lehman				
Firm-level controls	Yes	Yes	Yes	Yes
Product group FE	No	Yes	No	No
First-stage F statistics	32.7	17.8	67.1	26.5
$E[\Delta \ln Y: (-\Delta L_{p90}) - (-\Delta L_{p10})]$	-51.8	5.25	11.3	-38.2
Observations	992	1658	1286	1453

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For the firm-level regression in columns (1), (3), and (4), the standard errors are clustered by the three-digit NAICS, the regression is weighted by initial Y_f , and the firm-level controls are a firm's listed status, two-digit NAICS FE, number of loans, multi-lead FE, loan spread, number of loans due in the post-Lehman FE, and bond rating. For the firm-group-level regression in column (2), the cluster groups of standard errors, regression weights, and control variables are identical to the specification used in Table IV.

Table V clearly shows the importance of inventory in generating an output price fall due to the adverse credit supply shock. If one thinks of employment as a proxy for production, then the firms that face a negative credit supply shock decrease their production based on column (4).³¹ Without inventories, such firms that reduce their production would not have enough products to supply the market and would likely increase their output prices at the equilibrium. This reaction of firms is a conventional shift in the supply curve effect that leads to a rise in output prices. However, with inventories, such firms still increase their market share or sales (column (2)), because they draw down their inventories (column (1)) to provide an additional supply of products and accumulate cash (column (3)) from the product market. Inventory plays the role of a wedge or gap between the sales and production and makes production and sales move in opposite directions, which thus changes the direction of output price movements. Note that the increase in market share is small, despite

29. I report only the regression results instrumented with the measure of Lehman exposure in Table V, but the qualitative results are consistent if I use other credit supply shock measures.

30. In Online Appendix S5, I analyze with Compustat data the part of the inventory that is affected by the credit supply shock. The effect on inventory mainly comes from the final-good inventory and raw materials inventory.

31. Measuring production as sales minus inventory and regressing this measure on the credit supply shock similarly shows that the firms that face a negative credit supply shock decrease their production.

a large decrease in prices and inventory. In Online Appendix [S2.B](#), I present supporting evidence that a fall in firm-level product quality due to the negative credit supply shock lowers the market share, which partially counteracts the positive effect of the price changes on the market share.

In addition, I utilize the initial inventory and liquidity position across firms and industries together with the credit supply shock measure and find that the results also support the inventory adjustment hypothesis. The next section discusses this analysis in detail.

IV.B Heterogeneous Treatment Effect

I exploit the rich firm heterogeneity and group heterogeneity in the sample and estimate the heterogeneous treatment effect to provide additional insights and confirm the empirical findings in the previous section. I use the following regression specification:

$$(9) \quad \Delta \ln \tilde{P}_{fg} = \lambda_g + \beta_1(-\Delta L_f) \times Z_{fg} + \beta_2(-\Delta L_f) + \beta_3 Z_{fg} + \theta X_f + \varepsilon_{fg}$$

where Z_{fg} represents the firm-level or firm-group-level characteristics, such as inventory or cash holdings, before 2007. The only difference between this specification and equation [\(6\)](#) is the presence of Z_{fg} , which allows the effect of a credit supply shock on output prices to vary across the firm and group characteristics. The major assumption that I make in this regression is that firms or industries do not anticipate the sudden drop in their previous lenders' bank health after the Lehman failure and thus do not endogenously hold more Z_{fg} to hedge against this particular credit supply shock. Given that the Lehman failure in 2008 was surprising and that the signs of the mortgage crisis became apparent in 2007, this assumption is plausible. Note that the coefficients β_2 should be interpreted with caution since, with the exception of indicator variables, Z_{fg} is always positive.

First, I provide additional supports for the fire sale of inventory hypothesis, as shown in panel A of Table [VI](#). According to the hypothesis, firms that had a large amount of inventory before the Lehman failure should drop their prices more aggressively than firms with small initial inventory because the firms with a large amount of inventory have more inventory to sell. I test this prediction by using the variation in the 2006 inventory holdings conditional on initial sales.³² The effect of the negative credit supply shock is stronger by approximately 5.3 percent if firms hold one additional percent of inventory stock, consistent with the hypothesis. The key assumption that firms did not store inventory in preparation for the credit crunch is supported in Table [II](#) and consistent with the model in Section [VI](#), where producers hold inventories to avoid the stock-out of products. Given that this assumption is more plausible at the industry level, I also use an industry-level initial inventory and confirm this finding in column (2) of Panel A in Table [VI](#).

The inventory adjustment hypothesis also predicts that to ensure cash flow, the firms that are in urgent

32. The credit supply shock interacted with firm-group-level initial sales is controlled to compare the firms that generate similar sales. Similarly, for the industry-level regression, I controlled the initial industry-level value of shipment. This specification is more general than the specification that uses the conventional measure of inventory-to-sales ratio, which restricts the elasticity of inventory on price to be the same as the negative elasticity of sales on price. As shown in Online Appendix [S5](#), the importance of the raw material inventory suggests the need for such a generalization.

TABLE VI
HETEROGENEOUS TREATMENT EFFECT

	(1)	(2)	(3)	(4)
$\Delta \ln \tilde{P}_{fg}$: 2006q4-2007q2 to 2008q4-2009q2				
Panel A: Inventory and Liquidity				
Z_f	Inventory	Ind. inventory	RZ index	Loan due
($-\Delta L_f$) $\times Z_f$	-5.26*** (0.90)	-16.98*** (5.17)	-7.50*** (2.29)	-11.38** (5.69)
($-\Delta L_f$)	-0.67 (11.91)	10.10 (53.86)	-11.89*** (4.08)	-5.67*** (2.12)
Firm-level controls	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes
Observations	808	496	496	1797
Panel B: Alternative Financing and Size				
Z_f	Bond access	# of lead lenders	Total asset	Employment
($-\Delta L_f$) $\times Z_f$	5.83** (2.73)	1.98** (0.99)	9.00*** (1.46)	6.52*** (0.92)
($-\Delta L_f$)	-5.91*** (2.23)	-10.63** (4.33)	-137.33*** (22.69)	-63.02*** (10.22)
Firm-level controls	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes
Observations	1800	1800	834	834
Panel C: Demand Elasticity				
Z_{fg}	Elasticity w/ Bertrand		Elasticity w/ Cournot	
($-\Delta L_f$) $\times Z_{fg}$	-1.62** (0.69)	-1.64** (0.74)	-2.08*** (0.77)	-2.24** (0.86)
($-\Delta L_f$)	1.46 (2.26)		2.17 (2.36)	
Firm-level controls	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Product group FE	Yes	Yes	Yes	Yes
Observations	1800	1764	1800	1764

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, and the regression is weighted by initial sales. The firm-level controls are the firm's listed status, four-digit NAICS FE, bond rating, number of loans, amount of loans, loan type, loan-year FE, # of multi-lead and multi-lead FE, number of loans due in the post-Lehman FE, loan spread, loan maturity, firm age, and pre-Lehman market share. For columns (1) and (2) of Panel A, ($-\Delta L_f$) interacted with firm-group-level 2006 sales and the NAICS 4-digit value of shipment are additionally controlled, respectively. Inventory is firm-level 2006 log inventory, ind. inventory is NAICS 4-digit 2001-2006 average log inventory, and the RZ index is the NAICS 4-digit external financial dependence index as in [Rajan and Zingales \(1998\)](#). Loan due is a dummy variable that equals 1 for the firms that borrowed these loans, which matured in the post-Lehman period, before the post-Lehman period. Bond access is a dummy variable for the firms that issued bonds before the post-Lehman period, and # of lead lenders denotes the number of lead lenders for the last pre-Lehman loan. Elasticity is the demand elasticity under the nested CES demand system and different market structures (Bertrand and Cournot), as in the [Appendix](#) and [Hottman, Redding, and Weinstein \(2016\)](#).

need of cash should drop their prices more aggressively than the firms with a large amount of liquidity. I find that when they face a negative bank shock, cash-poor firms—companies with a small amount of cash in the pre-Lehman period—decrease their output prices more than their counterparts, as shown in Table [IX](#). This result also holds at the industry-level. As shown in column (3) of Panel A in Table [VI](#), when they face the negative credit supply shock, the firms in industries that lack internal liquidity decrease their prices more than their counterparts. Moreover, I find that the effect is stronger for the firms that had to pay out their loans in the post-Lehman period, as shown in column (4) of Panel A in Table [VI](#). Given that the Lehman failure was a surprise, firms that had to pay out their debts are likely to suffer more from financial problems and decrease their prices more to liquidate inventories and generate extra cash flow ([Almeida et al. 2012](#)). These analyses support the notion that firms sell off inventory to ensure their liquidity when they face an exogenous increase in the cost of external finance.

Additionally, as shown in panel B of Table [VI](#), the effect of the credit supply shock is weaker for the firms that issued a bond or had multiple lead lenders in the pre-Lehman period. These results show that the bank shock is less damaging to the companies that can rely on an alternative source of financing or alternative banks. Moreover, consistent with the studies that find that the effect of credit supply shock is larger for small companies, the effect is stronger for the firms that had smaller total assets and fewer employees (e.g., [Gertler and Gilchrist 1994](#); [Duygan-Bump, Levkov, and Montoriol-Garriga 2015](#)). These results are consistent with previous studies and confirm the validity of the credit supply shock measure used in this article.

Finally, I explore the heterogeneous demand elasticity across firms and product groups and find that the decrease in output prices due to the negative credit supply shock is larger for the firms that face high demand elasticity, as shown in panel C of Table [VI](#). Allowing firm fixed effects does not alter this result, which suggests that among its various product categories, a firm chooses to decrease the price of products for which demand is more elastic. This result is intuitive, as firms would receive a larger cash flow from the product market by lowering their prices when they face more elastic demand.³³ The estimated elasticities in the regression analysis are based on the nested CES demand system in the [Appendix](#), and the results are robust to different market structure assumptions.³⁴ Note that for panel C, I used the utility-based ideal price index along with the demand elasticities to coherently conduct the analyses within a nested CES demand framework. Other results are robust to using the utility-based price index.

V RECONCILIATION WITH GILCHRIST ET AL. (2017)

The results in this paper appear to be inconsistent with the results in [Gilchrist et al. \(2017\)](#), who conclude based on their empirical findings that financially-constrained firms raise their output prices relative to the

33. Of course, such firms might have less incentive to lower their prices. If firms that face a negative bank shock aim to generate a particular amount of sales, then the effect might be stronger for the firms that face an inelastic demand, as such firms have to decrease prices more to generate the targeted amount of sales. However, the reduced-form empirical results in this article do not support this prediction.

34. The derivation of demand elasticity under different market structure assumptions are in Appendix A of [Hottman, Redding, and Weinstein \(2016\)](#). I also tried the same regression with the HHI index and concentration ratio to understand how the effect differs across the degree of competition, but the estimated coefficients are not statistically significant enough to infer anything conclusive. I also measured and used the durability index but did not find statistically significant results.

prices of their counterparts. I argue that my empirical analyses and the inventory mechanism, in fact, are fully consistent with their results that firms with a small amount of liquidity (or in a “weak liquidity position”) raise their output prices. The difference between these two studies lies in the interpretation of the empirical results.

I first replicate and confirm their results in my sample by using their measure of financial constraint, liquidity:

$$(10) \quad \Delta \ln P_{fg} = \beta_0 + \eta_1 \text{LIQ}_f + \eta_2 X_f + \varepsilon_{fg}$$

where LIQ_f stands for liquidity, which is either contemporaneous (2008) cash to total assets or lagged (2006) cash to total assets. A fundamental difference relative to equation (6) is the *measure* of the credit supply shock. My baseline specification follows [Gilchrist et al. \(2017\)](#) closely and includes a lagged log change in sales, a lagged log change in the cost of goods sold, and the initial inventory-to-sales ratio as control variables (X_f). These controls aim to address the concerns related to the change in output prices, such as a change in demand, cost, and the inventory of firms. I additionally control the lagged dependent variable, similar to their measure of the lagged industry-level inflation. Given the limited availability of some control variables, following the previous study, I restrict my sample to listed firms.

TABLE VII
THE EFFECT OF CORPORATE LIQUIDITY ON OUTPUT PRICES

	(1)	(2)	(3)	(4)
$\Delta \ln P_{fg}$: 2006q4-2007q2 to 2008q4-2009q2				
	Including X_f related to			
	Gilchrist et al. (2017)		Bates, Kahle, and Stulz (2009)	
2006 LIQ_f	-2.84** (1.40)	-2.17* (1.21)	0.43 (2.14)	0.04 (2.16)
$(-\Delta L_f)$		-1.99** (0.94)		-3.37** (1.40)
2006 Cash Flow Volatility			-2.20** (0.93)	-2.15*** (0.79)
Observations	947	947	947	947

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, and the regression is weighted by initial sales. 2006 LIQ_f is the cash to assets in 2006, and 2006 Cash Flow Volatility is defined as a standard deviation of cash flow to assets for the past ten years. The set of firm-level controls related to [Gilchrist et al. \(2017\)](#) are the firm-level 2006 inventory to sales, the 2004-2006 change in market share at the firm-group-level, and the 2004-2006 change in the number of employees. The set of firm-level controls related to [Bates, Kahle, and Stulz \(2009\)](#) are the 2006 capital expenditure to assets, 2006 acquisitions to assets, and 2006 debt to assets. Across all specifications, the quality-adjusted utility-based price index is used, and the lagged dependent variable is included, similar to what had been done in [Gilchrist et al. \(2017\)](#), who use the quality-adjusted price index and control the lagged industry-level inflation. All reported variables are normalized to have a unit variance to facilitate the comparison of coefficients.

Even in my sample, the firms that had a large amount of cash before or during the banking crisis lowered their output prices relative to the output prices of their counterparts. Table [VII](#) reports the results by using the lagged liquidity, which is perceived to be more exogenous compared to the contemporaneous liquidity position. Based on column (1), a coefficient of lagged liquidity position is negative and statistically significant at the conventional level, which confirms the results in [Gilchrist et al. \(2017\)](#). The same replication results hold with the contemporaneous liquidity position, as shown in Online Appendix [S7](#). Column (2) additionally allows the measure of the bank shock, and in this specification, both the bank shock and liquidity independently explain the output price dynamics. These results confirm that the key difference in this article relative to the previous study is the measure of financial constraint, not the sample or regression specifications.³⁵

However, the effect of corporate liquidity is sensitive to the inclusion of other proxies of financial constraint, especially cash flow volatility. Since [Bates, Kahle, and Stulz \(2009\)](#) document the correlation between liquidity and other variables, which might confound the effect of liquidity on output price, column (3) considers an alternative set of control variables: initial cash flow volatility, capital expenditure to assets, acquisitions to assets, and debt to assets. In this specification, the coefficient of liquidity changes sign and loses the conventional level of statistical significance. In particular, the results suggest that the firms faced with larger cash flow volatility happened to hold more liquidity initially, and during the financial panic, they lowered their output prices; the cash flow volatility negatively affects price and takes over the effect of the liquidity in columns (1) and (2). Column (4) allows the bank shock in addition to cash flow volatility and other controls. Although the bank shock and the cash flow volatility separately explain output price growth, the liquidity still has no meaningful effect on output prices. Online Appendix [S7](#) considers a similar exercise with both listed and unlisted firms along with controls used in Table [IV](#). Both the bank shock and the liquidity affect output price dynamics without control variables, but after adding the controls, the coefficient of bank shock becomes larger and remains statistically significant, as in Table [IV](#), whereas the coefficient of initial liquidity changes sign and becomes statistically nonsignificant, as in Table [VII](#).

The unstable estimated coefficient of the corporate liquidity supports the view in the corporate finance literature that corporate liquidity is endogenously allocated across firms and cannot be used as a measure of financial constraint. In fact, by adopting corporate liquidity as a dependent variable in their regression analyses, a vast body of literature asks why companies hold liquidity. [Almeida et al. \(2014\)](#) survey this literature and conclude that firms hold more liquidity because they are *more* likely to be financially constrained. This argument dates back to [Keynes \(1936\)](#), who discusses that there is a fundamental relationship between corporate liquidity management and financial friction and emphasizes the precautionary saving motive to explain the variation in corporate liquidity position.

More specifically, consider the contemporaneous (2008) liquidity position. [Kahle and Stulz \(2013\)](#) find that the bank-dependent firms that were likely to be more affected by a credit shortage raised—not lowered—their liquidity in 2008. I confirm [Kahle and Stulz \(2013\)](#)’s finding by showing that the companies

35. In addition, as shown in Online Appendix [S6.H](#), the main result in this article is robust to using only listed firms under my preferred specification. Note that the timing of the event cannot explain the difference between the two studies. Consistent with this article, [Gilchrist et al. \(2017\)](#) focus on the period of Lehman failure as shown in their figures and tables.

that face a negative credit supply shock raise their liquidity, as shown in Table V. This result is consistent with the fire sale of inventory hypothesis and reflects that such firms want to sell their inventory to hold more liquidity due to the precautionary motive. However, such companies that face a negative bank shock would then be classified as firms in a strong liquidity position, not as firms in a weak liquidity position.

Regarding the lagged (2006) liquidity position, although it cannot be an outcome of the 2007-2009 financial crisis, there is still the question of why some firms held more liquidity than their counterparts in the pre-crisis period. By using the 2006 liquidity, I replicate a seminal work by [Bates, Kahle, and Stulz \(2009\)](#) and find that the firms that have more liquidity are likely to be *more* financially constrained relative to their counterparts before the financial panic. [Bates, Kahle, and Stulz \(2009\)](#) identify more than ten factors that lead firms to hold more liquid assets. In particular, they find that more cash holding (or a “strong liquidity position”) is associated with less investment, borrowing, acquisitions, and unstable cash flow, which are characteristics that likely reflect constrained companies rather than unconstrained companies. Table VIII confirms that their results hold in 2006, consistent with the results in Table VII. In Online Appendix S7, by reporting the same relationships between 2006 corporate liquidity and 2008 firm-level characteristics, I provide suggestive evidence that such firms kept constrained in the middle of the financial crisis. In this replication analysis, I use the Compustat database, which is used in [Bates, Kahle, and Stulz \(2009\)](#) and [Gilchrist et al. \(2017\)](#).³⁶ This result, along with previous studies, emphasizes that the concern on using liquidity as a measure of financial constraint is not specific to the particular sample that I use but generally applies to different data and periods. More generally, this concern is consistent with the findings in [Farre-Mensa and Ljungqvist \(2016\)](#), who show that the measures of financial constraint made with firm-level balance sheet variables do not correctly identify the true level of financial constraint.

Instead of using liquidity as an exogenous explanatory variable, to improve the identification strategy used in equation (10), I additionally include the measure of the bank shock and interact it with the 2006 liquidity, as in equation (9). Although both the discussion of the previous literature and the regression analyses in this section show the drawbacks of using the cash to assets as a financial *shock*, simultaneously, it could be a good measure of *responsiveness* to the bank shock. Based on previous studies, Tables VII, VIII, and the results in Online Appendix S7, it is likely that financially-constrained firms choose to hold a larger amount of liquidity before the financial crisis and were kept more constrained in the Great Recession than their counterparts. However, as a result of holding more internal liquidity, all else being equal, such firms would be less sensitive to the drying up of external funds.³⁷ By adding and interacting the bank shock with the initial liquidity, I seek to stress the benefit of liquidity, which is the mitigation of the effect of the external credit crunch, rather than other characteristics of liquidity. This identification strategy is similar to the strategy in [Jeenas \(2019\)](#), who uses the interaction of the firm-level initial cash holding and the exogenous aggregate monetary policy shock.³⁸

36. I closely follow [Bates, Kahle, and Stulz \(2009\)](#) for the cleaning of the Compustat database. See Online Appendix S4 for a more detailed discussion of the Compustat data used in this analysis.

37. Note that such a hedging role of cash holding is fully consistent with the interpretation of cash holdings in [Gilchrist et al. \(2017\)](#) and in other papers that utilize the initial cash holding as an independent variable, such as [Bacchetta, Benhima, and Poilly \(2019\)](#) and [Melcangi \(2019\)](#).

38. Another way to think about equation (10) is that initial liquidity is used as a measure of the responsiveness to the 2008-2009

TABLE VIII
CORPORATE LIQUIDITY AND FIRM-LEVEL CHARACTERISTICS IN YEAR 2006

	(1)	(2)	(3)	(4)	(5)
	Cash to assets				
Cash flow volatility	0.47*** (0.10)				0.14*** (0.04)
Capital expenditure to assets		-1.33*** (0.24)			-0.89*** (0.25)
Acquisition to assets			-0.71*** (0.13)		-0.53*** (0.06)
Debt to assets				-0.45*** (0.05)	-0.40*** (0.04)
Firm-level controls	No	No	No	No	Yes
Observations	1701	1701	1701	1701	1701

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by the two-digit SIC industry code. The firm-level controls are the 2-digit SIC, firm size, market to book ratio, networking capital to assets, dividend dummy, and R&D to sales. The construction of the variables and the choice of control variables follow [Bates, Kahle, and Stulz \(2009\)](#) closely, as reported in Online Appendix [S4](#).

As reported in column (1) of Table [IX](#), although firms decrease their output prices when they face a negative bank shock, the effect is smaller when firms have more initial liquidity. An increase in one percentage point of the 2006 cash to assets ratio mitigates the effect of the bank shock by approximately 1.14 percent. The qualitative result is robust to using three alternative measures of bank shocks, as shown in columns (2)-(4) of the same table. This result additionally clarifies how the main results in this article are related to the results in [Gilchrist et al. \(2017\)](#). The unconditional effect of initial corporate liquidity on output prices might be negative, as in Table [VII](#), since financially-constrained firms prefer to hold more initial liquidity and lower their output prices and inventory stock relative to their counterparts. However, conditioning on the negative bank shock, as shown in Table [IX](#), the effect of liquidity on the output price is positive, because more initial liquidity can ironically benefit firms in alleviating the external financial stress in the middle of financial crisis. These results are consistent with the interpretation that financially-constrained firms decrease their output prices.³⁹

financial crisis. However, to use the 2008-2009 financial crisis as a shock, one needs to make a strong assumption that other events in the same period did not differentially affect the firms that have more initial liquidity. For example, if a fall in the aggregate demand or a rise in the aggregate uncertainty in the same period differentially affects the risky firms that had high cash flow volatility, the coefficient of initial liquidity would be biased, as shown in Table [VII](#), since liquidity and cash flow volatility are positively correlated, as shown in Table [VIII](#). Such narratives potentially explain why, as shown in Online Appendix [S7](#), the firms that have more liquidity in 2006 were likely to be kept constrained during the financial crisis. Instead of using 2008 as a financial shock, equation [\(9\)](#) adapts the bank shock to separate the external financial shock from other events that happened in 2008.

39. Another way to modify equation [\(10\)](#) to address the endogeneity concern is to include additional control variables, which are likely to correlate with the 2006 liquidity and simultaneously affect the output price during the Great Recession. However, given that there are many variables that are correlated with the liquidity position as shown in [Bates, Kahle, and Stulz \(2009\)](#), it might

TABLE IX
TREATMENT INTERACTION: BANK SHOCK AND CORPORATE LIQUIDITY

	(1)	(2)	(3)	(4)
$\Delta \ln \tilde{P}_{fg}$: 2006q4-2007q2 to 2008q4-2009q2				
	Negative bank shock measured with			
	(- ΔL_f)	Lehman	ABX	(-BankItem)
Negative bank shock \times LIQ_f	1.14*** (0.31)	5.10*** (0.65)	2.28** (1.14)	0.63*** (0.10)
Negative bank shock	-12.85** (5.99)	-18.69*** (2.42)	-19.27** (9.20)	-9.73*** (1.40)
Firm-level Controls	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes
Observations	832	832	832	832

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group; and the regression is weighted by initial sales. The firm-level controls are the firm's listed status, four-digit NAICS FE, age, size, bond rating, number of loans, amount of loans, loan type, loan-year FE, multi-lead FE, number of loans due in the post-Lehman FE, loan spread, and loan maturity. The Lehman exposure, ABX securities exposure, and bank items are used as direct measures of bank shock. Similar to my treatment of the main leave-one-out credit supply shock measure, for consistency, I change the sign of the bank items. All four bank shock measures are standardized to have a unit variance. The year 2006 cash to assets variable in percentage points is used to ease the interpretation.

Moreover, Table IX provides additional support to the inventory adjustment hypothesis. Before the financial panic, companies originally had two sources of liquidity to manage their operations: internal liquidity (cash) and external liquidity (banks). When there is a surprising increase in the external cost of funding, the firms that had a large amount of cash at the beginning of the period would not need to sell off their inventory and decrease their price to generate extra cash. However, the firms that lack internal liquidity are more likely to sell their inventories and decrease their output prices to ensure extra funds. The results emphasize the rich interaction of output price, corporate inventory, and corporate liquidity in the middle of the financial crisis.

VI AGGREGATE IMPLICATIONS

To provide a back-of-the-envelope calculation for the effect of the credit supply shock on aggregate inflation dynamics through the inventory adjustment mechanism, this section presents a streamlined discussion of a simple business cycle model that relates the micro-level estimates to aggregate inflation dynamics.

be difficult to generate enough variation in this variable to consistently estimate the effect of liquidity when all of these variables are controlled. Indeed, in my sample, when I include 2006 liquidity and other variables in the regression, as shown in Table VII and Online Appendix S7, the estimated coefficient of liquidity loses statistical significance. Moreover, a bigger concern is the unobserved characteristics that cannot be easily measured in the data but potentially bias the effect of the 2006 liquidity on output prices. Note that I cannot use the credit supply shock as an instrumental variable for the liquidity measure because of the violation of an exogeneity condition. Under the inventory adjustment hypothesis, the credit supply shock does not affect the output price through only corporate liquidity.

Although the reduced-form micro-level regression framework with bank shocks is useful for identifying the credit supply shock with a minimal number of assumptions, these results can speak only to a relative change in the variable dynamics of interest because of the framework's reliance on the cross-sectional variation in the data. To analyze the aggregate dynamics, I include in the model two identical groups of producers that face different degrees of a credit supply shock. This formulation allows me to take advantage of micro-level empirical evidence to calibrate the parameters in the model, and through the lens of the model, I address the aggregate variable dynamics.⁴⁰ Online Appendix S1 illustrates the model in detail along with other simpler models that formalize the relationships among output prices, inventory, and the credit supply shock.⁴¹

There are five types of agents: households, retailers, a central bank, and two otherwise identical representative entrepreneurs that face different degrees of credit supply shocks. With the exception of the entrepreneurs, who are counterparts to the producers studied extensively in the micro-level data, the modeling of agents follows the canonical monetary business cycle model presented in Iacoviello (2005). Both the households and the entrepreneurs maximize their lifetime utility subject to their budget constraint. The households consume the final goods purchased from the retailers, lend to the entrepreneurs, work for the entrepreneurs, and earn wages in compensation. The entrepreneurs consume the final goods purchased from the retailers, borrow from the households, and produce the intermediate goods by hiring the households and using their capital stocks. The retailers use what they purchase from the entrepreneurs, differentiate the products, and sell to the consumers. In this process, the retailers face Calvo-Yun price rigidity in changing their output prices. The central bank is assumed to follow the standard Taylor rule in the main body of the paper, but Online Appendix S1.B discusses the amplifying role of the zero-lower bound observed in the Great Recession.⁴²

There are two fundamental features of the entrepreneurs that aim to match the micro-level empirical evidence. First, to integrate the fire sale of inventory hypothesis, I adapt the product stock-out motive of inventory holding, as described in Wen (2011).⁴³ I assume that entrepreneurs produce a continuum of products and that each product faces an idiosyncratic shock. The shock is realized after entrepreneurs produce their products, and this timing lag gives them an incentive to store products in inventory to avoid product stock-outs.

Second, to mimic the negative credit supply shock in the empirical analysis, entrepreneurs face the borrowing capability that is exogenously given to them. The thought experiment is the following: given a sudden decrease in one representative entrepreneur's borrowing capacity, how the output price and inventory dynamics of one entrepreneur evolve compared to that of the other entrepreneur. Once I calibrate the

40. This framework is similar to the framework of Nakamura and Steinsson (2014), who also exploit cross-sectional variation to estimate the key parameter and relate it to the aggregate variable (multiplier) by using the business cycle model.

41. Online Appendix S1.A shows a simpler version of the model that captures the dynamics of the relative variables without price rigidity and a central bank, and Online Appendix S1.C shows an analytical example of the partial equilibrium model of (S,s) inventory holding presented in Alessandria, Kaboski, and Midrigan (2010b)

42. To motivate a zero lower bound, I fix the interest rate for four quarters and then allow it to follow the Taylor rule. This analysis makes the effect of the decrease in the borrowing capability of the entrepreneur on aggregate inflation even stronger since the central bank cannot use monetary policy to counteract the deflationary force generated by the inventory adjustment mechanism.

43. One way to think about the model is the integration of the stock-out avoidance motive of inventory holding developed by Wen (2011) into a simple version of the business cycle model presented in Iacoviello (2005).

magnitude of the change in the entrepreneur's financial capability based on the output price's relative changes, which is 15 percent, I use the same shock to understand the behavior of aggregate inflation and inventory dynamics.⁴⁴ All other parameters in the model are calibrated to match the aggregate moments following the literature and are documented in Online Appendix S1.A.⁴⁵ Note that consistent with the empirical results in Table II, entrepreneurs do not hold inventory in preparation for the borrowing constraint in the model.⁴⁶

The key intuition of the model is the consumption smoothing motive of a representative entrepreneur that face a decrease in her borrowing capability.⁴⁷ Such constrained entrepreneurs face a decrease in consumption in this period due to the tightening of the borrowing constraint. To smooth their consumption, they sell off their inventory at a low price and generate extra sales from the product market. However, subsequently, they run out of inventory and increase their output prices. This behavior generates the temporary decrease in relative output prices and inventory observed in Figure III and Table V, as shown in Online Appendix S1.B.

Once I calibrate the magnitude of the relative change in borrowing capability based on the micro-level data, I look at how much the effect of such relative changes can explain the aggregate inflation dynamics in this canonical monetary business cycle model. To understand the counterfactual scenario where entrepreneurs do not decrease their inventory, I change the capital adjustment cost to evaluate the prediction without changing the steady-state. If the capital adjustment cost is high, entrepreneurs sell-off their inventory when they face a decrease in borrowing capability. However, when there is no capital adjustment cost, entrepreneurs instead decrease their capital investment and use these resources to increase their present consumption. Without a capital adjustment cost, it is more efficient for entrepreneurs to decrease their capital investment instead of their inventory stock since the decrease in inventory raises the probability of a product stock-out.

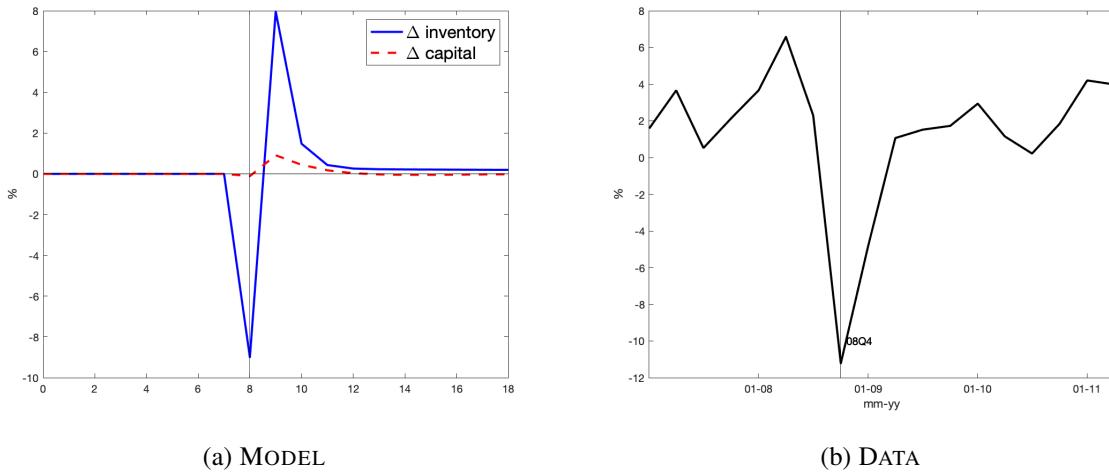
Figure V presents the predicted aggregate inflation dynamics with respect to the exogenous decrease in the borrowing capability of one type of entrepreneurs in the model along with the U.S. inflation dynamics observed in the data in the middle of the financial panic. In the benchmark case where entrepreneurs liquidate inventory to generate additional sales from the product market, when there is a decrease in the borrowing capacity of one of two representative entrepreneurs, there is an approximately 9% decrease in the aggregate inflation in the model followed by a similar increase in inflation. Considering the observed aggregate inflation in the data, such a borrowing shock can capture approximately 80% of the decrease in the short-run aggregate inflation in this period. However, subsequently, there is a large increase in aggregate inflation in the model, as entrepreneurs run out of inventory. Such a rise in inflation resembles the prediction of influential macro

44. To match the model with the data, I define an indicator variable that equals 1 if the measure of the credit supply shock is larger than the 50th percentile of the measure and equals 0 otherwise. I regress the change in log price on this measure and find that the effect of this indicator variable on output price is approximately 15%, as documented in Online Appendix S8.

45. Note that I do not match the parameters based on the consumer packaged goods because the objective of the model is to look at the aggregate dynamics. The external validity exercises reported in Online Appendix S6.K give justifications in looking at aggregate dynamics with the model. In addition, the movements in the aggregate series in this period, such as changes in prices, inventory, corporate cash holdings, and the credit condition, are consistent with the inventory mechanism and additionally support the generalization of the inventory mechanism.

46. Requiring entrepreneurs to hold inventory to avoid a credit crunch would likely amplify the inventory adjustment mechanism because there is more incentive for entrepreneurs to liquidate inventory when they face a negative credit supply shock.

47. For the listed companies, one can think of the dividend smoothing motive of producers, which is well documented in the studies of corporate financial policy (e.g., [Brav et al. \(2005\)](#)). [Bianchi and Bigio \(2018\)](#) also use such interpretations in modeling the consumption of bankers. Instead of using the consumption smoothing motive, it is likely that one can generate the inventory adjustment with respect to a financial shock by explicitly integrating the bankruptcy of producers.



THE AGGREGATE INFLATION DYNAMICS IN THE MODEL AND DATA

Note. The left-panel shows the predicted dynamics of aggregate inflation due to the negative credit supply shock.

Note. The left-panel shows the predicted dynamics of aggregate inflation due to the negative credit supply shock to one of two representative entrepreneurs in the model. The solid blue line reflects the aggregate inflation dynamics when producers sell their inventory to alleviate the effect of the credit supply shock, and the dotted red line is the aggregate inflation dynamics when producers decrease their capital investment instead of inventory to alleviate the credit supply shock. The right-panel shows the U.S. inflation dynamics observed in the data during the financial panic, which is calculated from the producer price index (PPIACO_PCH) made available by the Bureau of Labor Statistics.

models that explain the stable inflation in this period despite a large fall in aggregate demand (e.g., [Del Negro, Giannoni, and Schorfheide 2015](#); [Christiano, Eichenbaum, and Trabandt 2015](#); [Gilchrist et al. 2017](#)). To understand the stable inflation dynamics in this period, these models integrate the inflationary pressure of financial shock through various mechanisms other than the inventory adjustment. In contrast, the model presented in this article suggests that the inventory adjustment due to a similar financial shock generates inflationary pressure that follows the deflationary force. When entrepreneurs decrease capital investment instead of adjusting inventory, the financial shock has a negligible effect on the inflation dynamics since entrepreneurs do not need to lower their output prices to decrease their capital investment.

Overall, the simple business cycle model in this article emphasizes the importance of the inventory by providing a rough estimate for the effect of the credit supply shock on aggregate inflation dynamics with and without an inventory adjustment mechanism. The results should be interpreted with caution since the inflation in this period is affected by many other factors that are not explicitly modeled.⁴⁸ The impulse response function presented in Figure V should be interpreted as a back-of-the-envelope calculation for the effect of a financial shock on aggregate inflation dynamics with and without an inventory adjustment mechanism.

48. For example, a fall in housing prices, a rise in uncertainty, a fall in international trade, and a fall in oil and commodity prices are not present in the model. Other features, such as the input-output production network and the industry and firm heterogeneity in inventory holding, would also affect the quantification.

VII CONCLUSION

In this paper, by using novel micro-level data and a change in bank health at the time of the Lehman failure as an exogenous variation of companies' credit condition, I find that the firms that face a negative credit supply shock decrease their output prices. I posit a "fire sale" of inventory hypothesis to explain this empirical finding: firms that face a negative credit supply shock decrease their prices because they need to quickly sell off their inventories and generate extra cash. I empirically support this hypothesis by using both macro-level and micro-level data.

This paper reveals that the corporate inventory used for liquidity management, which has been neglected in previous studies on banking crises, is a crucial determinant of output price dynamics. Models that feature inventories will better account for the fluctuation of output prices, inventory, and other economic and financial variables.

APPENDIX

This section presents the results based on the utility-based price index. I adapt the nested CES demand system in [Hottman, Redding, and Weinstein \(2016\)](#) to build the firm-group-specific price index from the ACNielsen Homescan Panel database.

Consider the following Cobb-Douglas utility function:

$$(11) \quad \ln \mathbb{U}_t = \int_{g \in \Omega} (\varphi_{gt} \ln C_{gt}) dg, \quad \int_{g \in \Omega} \varphi_{gt} dg = 1$$

where subscript g is the product group, and t is time. Ω is the set for a product group, and φ_{gt} is a consumer's perceived product group quality (or appeal/taste) at time t . C_{gt} is the group-time-specific consumption index that corresponds to the following CES nests:

$$(12) \quad C_{gt} = \left[\sum_{f \in \Omega_{gt}} (\varphi_{fgt} C_{fgt})^{\frac{\sigma_g^F - 1}{\sigma_g^F}} \right]^{\frac{\sigma_g^F}{\sigma_g^F - 1}}, \quad C_{fgt} = \left[\sum_{u \in \Omega_{fgt}} (\varphi_{ut} C_{ut})^{\frac{\sigma_g^U - 1}{\sigma_g^U}} \right]^{\frac{\sigma_g^U}{\sigma_g^U - 1}}$$

where subscript f is the firm and u is the UPC or barcode-level product, Ω_{gt} is the set of the firms within product group g at time t , Ω_{fgt} is the set of the UPCs made by firm f in product group g at time t , φ_{fgt} captures perceived firm-group quality at time t , φ_{ut} captures the perceived UPC quality made by firm f in product group g at time t , σ_g^F governs the elasticity of substitution across firms for each product group, and σ_g^U governs the elasticity of substitution across UPCs for each firm.⁴⁹ Under this structure, firm appeal (φ_{fgt}^F) affects the sales of all products supplied by firm f within product group g *proportionately*, while product appeal (φ_{ut}^U) determines the *relative* sales of individual products u within firm f and product group g .

It is useful to illustrate the underlying consumer behavior with the nested CES demand system used in this article. When consumers visit a store, the demand system assumes that they first decide which product group they will buy from, then decide which brand or firm's product to purchase, and then purchase a specific UPC. For example, a consumer decides to purchase jams, jellies, or spreads (product group), then decides to buy a Smucker's product (firm), and then chooses Smucker's sugar-free strawberry-flavor fruit spread (UPC). The elasticities govern how sensitively consumers react to changes in the output price, and the perceived quality parameters govern how purchasing behavior is affected by factors other than output prices, such as product quality (e.g., organic vs. non-organic), brand quality, and product/brand advertisement.

49. As discussed in [Hottman, Redding, and Weinstein \(2016\)](#), φ_{fgt}^F cannot be defined independently of φ_{ut}^U because the utility is homogeneous of degree one in perceived firm quality. I normalize the quality parameter: $\tilde{\varphi}_{gt}^F = \left(\prod_{f \in \Omega_{gt}^F} \varphi_{fgt}^F \right)^{\frac{1}{N_{gt}^F}} = 1$, $\tilde{\varphi}_{fgt}^U = \left(\prod_{u \in \Omega_{fgt}^U} \varphi_{ut}^U \right)^{\frac{1}{N_{fgt}^U}} = 1$, where N_{gt}^F is the number of firms in product group g at time t and N_{fgt}^U is the number of UPCs made by firm f within group g at time t .

The corresponding well-known exact CES price indexes are

$$(13) \quad P_{gt} = \left[\sum_{f \in \Omega_{gt}} \left(\frac{P_{fgt}}{\varphi_{fgt}} \right)^{1-\sigma_g^F} \right]^{\frac{1}{1-\sigma_g^F}}, \quad P_{fgt} = \left[\sum_{u \in \Omega_{fgt}} \left(\frac{P_{ut}}{\varphi_{ut}} \right)^{1-\sigma_g^U} \right]^{\frac{1}{1-\sigma_g^U}}$$

and the expenditure shares of products are⁵⁰

$$(14) \quad S_{fgt} = \frac{\left(P_{fgt} / \varphi_{fgt} \right)^{1-\sigma_g^F}}{\sum_{k \in \Omega_{gt}} \left(P_{kgt} / \varphi_{kgt} \right)^{1-\sigma_g^F}}, \quad S_{ut} = \frac{\left(P_{ut} / \varphi_{ut} \right)^{1-\sigma_g^U}}{\sum_{k \in \Omega_{fgt}} \left(P_{kt} / \varphi_{kt} \right)^{1-\sigma_g^U}}$$

The above equation clarifies how this framework perceives UPC-specific and firm-specific qualities, φ_{ut} and φ_{fgt} . These qualities change the market share holding the output price constant. If two products have the same price but one has a larger market share, then this product has a higher perceived quality.

The relative market share can be derived from the following equation (14):

$$(15) \quad \frac{S_{ut}}{\tilde{S}_{fgt}} = \frac{\left(P_{ut} / \varphi_{ut} \right)^{1-\sigma_g^U}}{\left(\tilde{P}_{ut}^U / \tilde{\varphi}_{ut}^U \right)^{1-\sigma_g^U}}$$

where $\tilde{S}_{fgt} = \left[\prod_{u \in \Omega_{fgt}} S_{ut} \right]^{\frac{1}{N_{fgt}}}$, which is the geometric average of the market share of UPCs for firm f within group g at time t. By plugging (15) into (13), one can derive the following firm-group-time price index

$$(16) \quad \ln P_{fgt} = \underbrace{\ln \tilde{P}_{fgt}}_{\text{Standard Index}} - \underbrace{\frac{1}{\sigma_g^U - 1} \ln \left[\sum_{u \in \Omega_{fgt}} \frac{S_{ut}}{\tilde{S}_{fgt}} \right]}_{\text{Quality/Variety Correction}}$$

where the first term is the geometric average of the UPC-level price within the firm and the group, which is used in the main body of this article. This term is analogous to the standard price index, such as the Tornqvist or Laspeyres index. The second term is a variant of the Theil index, which measures quality and variety correction in the price index. Note that $\sum_u \frac{S_{ut}}{\tilde{S}_{fgt}}$ in the second term increases if (1) the number of UPCs by firm f within group g (N_{fgt}) increases (variety effect), or (2) the UPC share dispersion within the firm increases (quality effect).⁵¹

To measure the price index in equation (16), I use the estimated demand elasticities (σ_g^U) from [Hottman, Redding, and Weinstein \(2016\)](#).⁵² Identical to the main analysis, I take a geometric average across quarters

50. Equation (14) can be recovered by using Shephard's lemma.

51. The UPC share dispersion reflects the perceived product quality. For example, suppose that consumers see two products offered by the same firm at the same price. It is better for consumers to see one high-quality product and one low-quality product rather than two mediocre products because one can always choose a high-quality product in the former scenario, whereas they must always choose a mediocre product in the other scenario. This intuition is reflected in the share dispersion term, which measures heterogeneity in product quality.

52. [Hottman, Redding, and Weinstein \(2016\)](#) apply a modification of the “identification through heterogeneity” method originally

within 2006:Q4-2007:Q2 (the last three quarters in the pre-Lehman period) and 2008:Q4-2009:Q2 (the post-Lehman period) to make the price index comparable to the credit supply shock. I then take the difference of the logged price index across pre- and post-Lehman periods.

Table A.1 presents the results that replicate Table IV with the utility-based firm-group-specific price index in equation (16). All the coefficients are negative and statistically significant, and the magnitudes of the estimated coefficients are similar to the magnitudes of the estimated coefficients in Table IV. The results are robust to other price indexes, as reported in Online Appendix S6.G.

TABLE A.1
MAIN RESULTS WITH THE UTILITY-BASED PRICE INDEX

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln P_{fg}$: 2006q4-2007q2 to 2008q4-2009q2						
	OLS		(- ΔL_f) instrumented using			
(- ΔL_f)	-2.25*** (0.76)	-8.57*** (1.46)	-7.32*** (2.66)	-7.00*** (2.53)	-8.80*** (3.01)	-7.88*** (1.73)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
product group FE	No	Yes	Yes	Yes	Yes	Yes
naics 4-digit FE	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			16.80	7.80	14.90	11.90
J-statistics p-value						0.89
$E[\Delta \ln P]$	11.379	11.4	11.4	11.4	11.4	11.4
$E[\Delta \ln P: \Delta L_{p90} - \Delta L_{p10}]$	-4.916	-18.7	-16	-15.3	-19.2	-17.2
Observations	1658	1658	1658	1658	1658	1658

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, the regression is weighted by initial sales, and the firm-level controls are the firm's listed status, age, bond rating, number of loans, amount of loans, loan type, loan-year FE, multi-lead FE, number of loans due in the post-Lehman FE, loan spread, loan maturity, and lagged $\Delta \ln P_{fg}$

developed by Feenstra (1994) to the same data set that I use in this paper. I am grateful to the authors for providing these estimates.

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