The Effect of the Credit Crunch on Output Price Dynamics: The Corporate Inventory and Liquidity Management Channel*

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July 31, 2018

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Abstract

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 firms facing a negative credit supply shock *decrease* their output prices approximately 15% relative to 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) firms facing 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 firms and sectors with high initial inventory or small initial cash holdings. To discuss the aggregate implications of these findings, I integrate this micro-level study into a business cycle model by explicitly allowing for two identical groups of producers facing different degrees of credit supply shock. The model predicts that a negative credit supply shock leads to a large *temporary* drop in aggregate inflation—as a result of the aggressive liquidation of inventory—followed by an increase in inflation as producers eventually run out of inventory. This prediction for inflation and inventory dynamics is fully consistent with observations for the 2007-09 recession.

*I am indebted to Emi Nakamura, Jón Steinsson, Jonathan Vogel, and David Weinstein for invaluable discussions, guidance, and support. I am grateful to Hassan Afrouzi, Hie Joo Ahn, JaeBin Ahn, Henrique Basso (discussant), Jeffrey Campbell, Chris Conlon, Olivier Darmouni, Andres Drenik, Matthieu Gomez, Katherine Ho, Colin Hottman, Jungsik Hyun, Yang Jiao, Yoon Joo Jo (discussant), Réka Juhász, Lorena Keller (discussant), Jennifer La'O, Mauricio Larrain, Jae Won Lee (discussant), Christian Moser, Andreas Mueller, Hyunseung Oh, Matthias Paustian, Ricardo Reis, Giacomo Saibene (discussant), Bernard Salanié, José Scheinkman, Stephanie Schmitt-Grohé, Samer Shousha, Joseph Stiglitz, Philip Strahan (discussant), Catherine Thomas, Martin Uribe, Daniel Villar, Daniel Wolfenzon, Michael Woodford, and participants in numerous seminars for helpful comments and suggestions. Part of this paper was written at the Federal Reserve Board while I was a dissertation intern. I thank Dave Harvey, Sue Hutchinson, and Jing Zhou for their help with the data collection and analysis. All errors are my own.

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1 Introduction

The questions of how and to what extent credit market disruptions affect the economy as a whole have been of vital interest in the macroeconomics and finance literature, particularly after the 2007-09 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 credit market stress following the September 2008 failure of Lehman Brothers, new loans to large borrowers dropped 79% relative to 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, breaking the previous record set after the 1987 Black Monday crash.

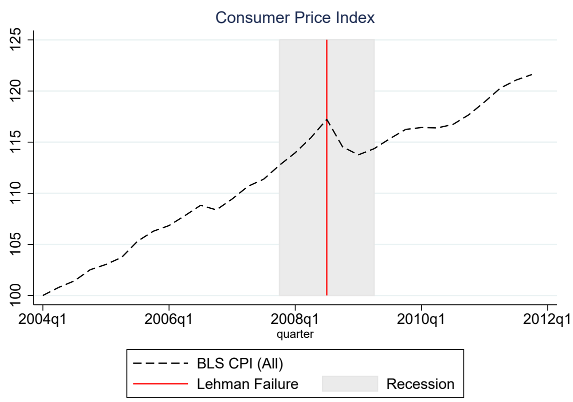
During these credit market disruptions, the producer price index plummeted approximately 15% in three months (Figure 1b).[1] Given this aggregate correlation, this article seeks to answer the following questions: Do firms that face a negative credit supply shock decrease their output prices? If so, why?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

Identification poses the biggest challenge in answering these questions. Although there is a clear positive correlation between inflation and credit market conditions in Figures 1a and 1b, it is difficult to identify the relationship between these series from the aggregate data. The aggregate correlation is based on the Great Recession, and conventional macroeconomic models can easily explain a decrease in inflation during the recession without relying on credit market conditions. Even worse, many influential events occurred at the same time, such as a fall in housing prices (Mian et al. 2013), a drop in oil prices (Hamilton 2009), and a decrease in international trade (Eaton et al. 2016), making aggregate time-series comparisons nearly impossible.

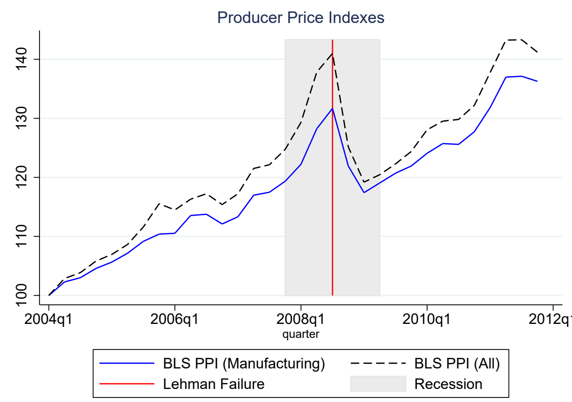
To overcome this identification challenge, I build a novel micro-level dataset that combines producers' prices and sales at the barcode level from the Nielsen Homescan Panel database with producers' balance sheet information from the Orbis database, and their loan market access from the Dealscan database. The merged dataset contains detailed information on prices and quantities sold by public and private firms and producers' banking relationships from 2004 to 2011. For example, if a household purchases Coke at a store, I observe the price and quantity of Coke purchased, Coca-Cola's balance sheet, and which bank Coca-Cola deals with. Because many papers discuss the importance of product entry and exit and changes in product quality for explaining changes in output prices (Nakamura and Steinsson 2012, Hottman et al. 2016), I adapt the nested constant elasticity of substitution (CES) demand system to incorporate the effects of

[1] Note that the core CPI (consumer price index excluding energy and food) did not fall as much during this period; thus, because of this stable core CPI, one might believe that a large fall in oil and commodity prices in this period entirely explains the decrease in the aggregate producer price index. However, a closer look at more disaggregated industry-level price data reveals a different picture. Like the aggregate price index, the manufacturing price index fell dramatically in this period, which is difficult to explain by a fall in oil prices and in the commodity price index. The price index for the service sector, which is notoriously difficult to measure, had been stable in this period, and this stability is the main reason for the core CPI's stability. Moreover, the price of oil itself is endogeneous with respect to economic fundamentals (Kilian 2014). The channel I propose in this paper can partially explain the movement of the oil price in this period, hence can additionally explain the aggregate price dynamics.

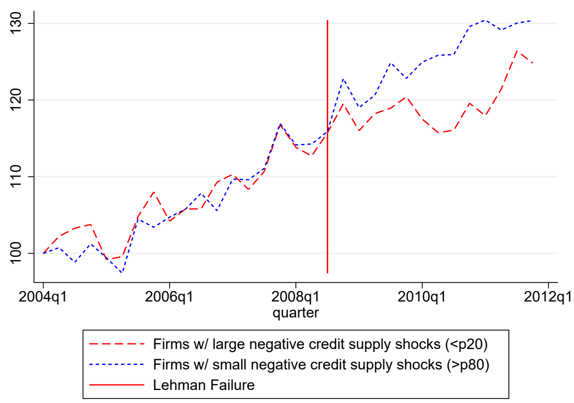
Figure 1: Output Price, Inventory, and Corporate Cash Holding after the Lehman Failure



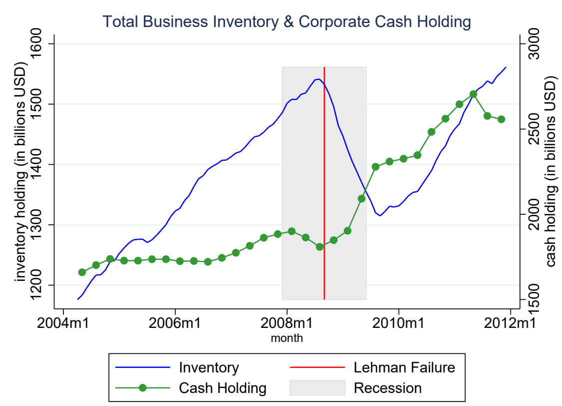
(a) Consumer price index



(b) Producer price indexes



(c) Differential change in the scanner price index



(d) Inventory and cash holding

Note. (a) plots the BLS aggregate consumer price index, while (b) plots the BLS aggregate producer price index and the producer price index for manufacturing sectors only. (c) shows the differential change in the price index between credit-constrained firms and their unaffected counterparts. (d) shows the total business inventory and corporate cash holdings. Details on variable measurement are given in Appendix B.

variety and quality change and thereby construct the price index for the main empirical analysis. To the best of my knowledge, this paper is the first to combine information on 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 firms facing a negative credit supply shock *decrease* their output prices approximately 15% more than their unaffected counterparts do. While 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 Zingales 1997) and Whited-Wu (Whited and Wu 2006) and conclude that they do not accurately identify financially constrained firms because they are constructed 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, I utilize a change in bank health at the time of the Lehman failure to generate plausibly exogenous variation in firm-level credit supply conditions. In addition to my main measure of change in bank health based on banks' loan issuance, I use three bank shock measures from Chodorow-Reich (2014) that are not highly correlated but give consistent results: banks' exposure to the Lehman failure, banks' exposure to toxic asset-backed securities, and bank balance sheet items, such as bank deposits and net trading revenues, which are unlikely to be correlated with borrowers' characteristics. These three measures affect firms' credit supply conditions for reasons that are plausibly orthogonal to their characteristics related to pricing decisions. Figure 1c illustrates the empirical results.

I hypothesize that firms facing a negative credit supply shock decrease their output prices by liquidating inventory and dumping their products in order to generate extra cash flow from the product market, and I provide strong empirical support for this hypothesis. I first show that at the time of the Lehman bankruptcy, there was an enormous decline in aggregate inventory and an increase in corporate cash holdings (Figure 1d). Then, using the micro-level data and the corresponding identification strategy, I find that firms facing negative bank shocks decrease their inventory relative to their counterparts. These firms decrease their output prices only temporarily and then increase output prices after about a year, which indicates 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, illustrating 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 firms or sectors that had larger inventories or smaller cash holdings before the Lehman failure, confirming 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 decrease their output prices in this conversion process.

Additionally, I estimate 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 firms facing negative bank shocks decrease their output prices more if (i) they face high product demand elasticity, (ii) they rely more heavily on the loan market, (iii) they did not issue a bond before the credit supply shock was realized, (iv) they had to pay out loans immediately after the Lehman failure, (v) they dealt with a small number of lead-lenders in the pre-Lehman period, or (vi) they are small in terms of employment or total assets. 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—firms would not be able to cut output prices to increase revenue. Other results are also intuitive and consistent with the literature since the effect of a credit supply shock is likely to be larger for 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 potential concerns relating to retailer decisions and purchaser characteristics, as well as variety-quality changes, external validity, changes in local conditions, foreign exposure, other price indexes, pre-trends, and sample weights.

I integrate the micro-level study into the business cycle model to formalize the underlying mechanisms in the empirical analysis and to analyze the aggregate inflation dynamics. 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 interested variable dynamics because of the framework's reliance on cross-sectional variation in the data. To analyze aggregate dynamics, I include in the model two identical groups of producers facing different degrees of credit supply shock. This formulation allows me to take advantage of micro-level empirical evidence to calibrate parameters in the model, and through the lens of the model, I address aggregate variable dynamics.[3] In particular, my model captures the relative changes in output price, inventory, market share, and employment due to the credit supply shock observed in the micro-level data.

I find that a "fire sale" inventory channel can explain the large drop in *aggregate* inflation and inventory that occurred at the peak of the financial panic, which was followed by surprisingly stable inflation. An exogenous decrease in the borrowing capability of one group of entrepreneurs

[2] Of course, firms facing high demand elasticity might have a lower 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 a little bit, 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.

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

led inflation to fall in the short run as these entrepreneurs aggressively liquidated their inventory. However, in the medium and long run, inflation increases in the model because firms cannot sell their inventory forever. This behavior in price dynamics is fully consistent with not only micro-level empirical evidence but also aggregate inflation dynamics amid a financial panic. There was a drop of more than 10% in the producer price index in the short run and surprisingly stable inflation in the medium run, despite a large increase in unemployment—the so-called missing disinflation puzzle discussed in the literature[4]—and the model generates both short- and medium-run inflation dynamics under a realistic calibration of parameters. The magnitude of the shock calibrated to match the micro-level data can explain almost all of the decrease in aggregate inflation during this period.

This paper highlights the importance of inventory dynamics—a topic that has largely been neglected in the literature—in explaining the aggregate inflation dynamics during the banking crisis. 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 cost—or other channels that lead companies to increase their prices due to financial friction. However, this increase in output price will be inconsistent with the micro-level empirical evidence in this article as well as with the aggregate inflation dynamics during this period if we believe companies' credit supply condition is an important determinant of the aggregate variables. The model that incorporates the inventory mechanism and the traditional effect will capture the large decrease in the price growth rate in the short run, which was followed by stable inflation despite the large increase in the unemployment rate during the banking crisis.

My findings are surprising because they seemingly conflict with the influential work of Gilchrist et al. (2017), who, 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 the different results arise from the difference in the measure, not the sample or regression specification. The results are presented in section 3.6.1. I use the liquidity positions in both 2008 (contemporaneous position) and 2006 (initial position) to study output price dynamics during the financial panic, consistent with Gilchrist et al. (2017).

A natural question is why different measures of financial constraint cause different results. Previous studies in the corporate finance literature raise a concern about using liquidity as a

[4]The literature discusses the missing disinflation puzzle in this period; the fact that inflation did not fall as much as predicted by the New Keynesian Phillips curve. Previous studies usually treat the short-run period as an outlier (2008:Q4 and 2009:Q1) and focus on the post-crisis period with jobless recovery or on the core CPI that reflects the service sector price index and hence abstracts away from a decrease in inflation during this period. The model in this paper is consistent with this literature, because the model generates an increase in inflation in the medium run.

measure of financial constraint. In their study on liquidity position, Kahle and Stulz (2013) find that firms facing a negative bank shock raised—rather than lowered—their liquidity in 2008.[5] This result is consistent with my findings and with my hypothesis that such firms convert inventory to cash or illiquid assets to liquid assets. Those firms that suffer from a negative bank shock would therfore be classified as firms in the "strong liquidity position" not the "weak liquidity position." Regarding the initial (2006) liquidity position, a seminal paper by Bates et al. (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, and acquisitions, and stable cash flow—characteristics that likely reflect unconstrained companies rather than constrained companies. I confirm the findings of Bates et al. (2009) using liquidity in the year 2006. More generally, 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 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).[6]

More broadly, this article is related to various papers that study financially constrained companies' pricing decisions. The so-called missing disinflation puzzle indicates that inflation did not fall as much in this period as predicted by the New Keynesian Phillips Curve (Ball and Mazumder 2011, Hall 2011, Coibion and Gorodnichenko 2015). A prominent hypothesis that explains this stable inflation is financial friction. Papers such as Del Negro et al. (2015), Christiano et al. (2015), and Gilchrist et al. (2017) incorporate financial friction into a business cycle model to explain inflation dynamics during the Great Recession. These papers rely on the cost-push channel or other effects of financial friction to explain the inflation dynamics, and the theoretical predictions in this article are consistent with their results if I do not incorporate the effect of inventory liquidation into the model. I seek to expand these previous studies by incorporating a fire sale inventory mechanism, which maintains consistency with the micro-level empirical evidence I find and with a sudden, dramatic, and temporary fall in inflation in this period. Papers on industrial organization and corporate finance also study this topic, but they are inconclusive regarding how financial distress affects output price, 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 Sertsios 2013), while others find the opposite result for retail industries (Chevalier 1995a, Chevalier 1995b, Chevalier and Scharfstein 1995, Chevalier and Scharfstein 1996). I complement this line of research by exploiting a new

[5]See Garcia-Macia and Villacorta (2016) for a theoretical formulation of such behavior.

[6]See Section 3.6.1 and Appendix D for more detailed discussion.

data-set with bank shocks that generates plausibly exogenous variations in companies' credit supply conditions.

This work highlights the importance of inventory in the business cycle model and is closely related to previous studies on inventory dynamics. Inventory is known to contain valuable information for business cycle research because of its volatility and pro-cyclical behavior (Ramey and West 1999). Previous studies examine inventory dynamics and the sources of cyclical fluctuation (West 1990), the slope of marginal cost (Ramey 1991), price-cost markup cyclicality (Bils and Kahn 2000, Kryvtsov and Midrigan 2013), international trade (Alessandria et al. 2010, Alessandria et al. 2011), international business cycles (Alessandria et al. 2013), and news shock (Crouzet and Oh 2016). Papers such as Khan and Thomas (2007) and Fisher and Hornstein (2000) incorporate inventory into the business cycle model to explain the salient feature of the data. Extending these studies, I integrate inventory into the business cycle model to explain short-run and medium-run inflation dynamics. In particular, I show that bank shock, which has rarely been addressed in this literature, can generate pro-cyclical inflation and inventory dynamics.[7] In doing so, I integrate the stock-out avoidance motive of inventory holding developed by Wen (2011) into a parsimonious business cycle model. The main components of my model are based on Iacoviello (2005) and include two groups of identical producers to explicitly reflect the micro-level empirical evidence.

The mechanism in this paper emphasizes that inflation dynamics can be explained by corporate inventory and liquidity management, which have been a prominent research area (Almeida et al. 2014). The most closely related papers to this study are the seminal work by Kashyap et al. (1994) and Gertler and Gilchrist (1994), who provide evidence that liquidity-constrained firms liquidate their inventories. Other papers, such as Carpenter et al. (1994, 1998) and Bates et al. (2009), also suggest a close link between corporate inventory investment and internal finance or corporate cash position. My findings also complement studies that examine how firms substitute between external financing and internal financing or between banks and cash (e.g., Campello et al. 2011, Lins et al. 2010, Sufi 2009). Studying liquidity management during the Great Recession, Kahle and Stulz (2013) find that bank-dependent firms that were likely to be more affected by a credit shortage accumulated more cash. While this paper is consistent with Kahle and Stulz (2013), it appears to conflict with Campello et al. (2010), who find that constrained firms burned through more cash. However, a definition of "constrained" in Campello et al. (2010) is based on a survey of chief financial officers (CFOs) and is likely different from bank shock. For companies to hold more cash because of a negative credit supply shock, the shock must be persistent such that companies expect to be more financially constrained in the next period and hence have a strong precautionary motive to hold more cash. A bank shock is likely to meet this requirement because it is not the current debt position of companies but

[7] Kashyap et al. (1994) and Gertler and Gilchrist (1994) study inventory dynamics in a similar context: monetary policy shock.

rather that of their insurers, who ensure liquidity in future periods. Overall, the inventory and liquidity management channel I propose is generally consistent with the literature, and I adapt this framework to understand output price dynamics.

For the empirical analysis, this paper draws on the methodologies in Chodorow-Reich (2014) and Hottman et al. (2016). To overcome the identification challenge, I use bank shock. Previous studies document that firms that cannot borrow from banks are likely to default (Khwaja and Mian 2008) and decrease their investment (Peek and Rosengren 1997, Peek and Rosengren 2000, Amiti and Weinstein forthcoming), employment (Greenstone et al. 2015), and exports (Amiti and Weinstein 2011, Paravisini et al. 2015). I use the identification strategy in Chodorow-Reich (2014) and Ivashina and Scharfstein (2010) but answer a different question with different data. To the best of my knowledge, this article is the first to look at the effect of a bank shock on output price behavior, especially through the inventory and cash management channel. In constructing a firm-group-level price index from scanner-level data, I adopt the nested CES demand system in Hottman et al. (2016) to adjust for the variety and quality effect. This system allows for a more flexible structure than the CES demand system (Atkeson and Burstein 2008, Edmond et al. 2015). The major advantage of this framework is its explicit adjustment of product quality and variety. In other studies, a similar adjustment has been made not only to measure the coherent price index and consumer welfare (Broda and Weinstein 2010, Atkin et al. forthcoming) but also to study the pattern of international trade (Feenstra and Romalis 2014), exchange rates (Nakamura and Steinsson 2012), business cycles (Jaimovich et al. 2017), and monetary policy (Schmitt-Grohe and Uribe 2012). This study draws on this important contribution to the literature to study output price dynamics during the banking crisis.

The rest of this paper is structured as follows: Section 2 explains the construction and description of the micro-level data, while Section 3 presents the micro-level empirical specification, identification strategy, and empirical results. Section 4 illustrates the business cycle model and theoretical results. Section 5 concludes.

2 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.

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.[8] 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, covering 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 10 demographic variables to make the sample nationally representative.[9] According to Nielsen, the Homescan Panel covers approximately 30 percent of all household expenditures on goods in the consumer price index (CPI) basket.

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 the comparison of similar products produced by firms facing different degrees of credit supply shock. Second, the dataset provides product sales information, which is useful to separate the quality component of product prices and to confirm that the effect is not driven by the change in product demand. Finally, these data record 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 to address other potential identification concerns related to the change in purchasers' income and employment, housing price, local conditions, and retailers' behavior.

I integrate the prices and quantities of each product with its producer's information using the GS1 US Data Hub, Orbis, and Fixed Income Securities Database (FISD). GS1 is the company that issues barcodes to producers.[10] Their data record the company name and address for each barcode-level product, providing a way to link barcode-level product information with its producer information. 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 firms' inventory and cash holdings, which are particularly helpful in testing the fire sale of inventory hypothesis. It also has information on 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. Like the Nielsen dataset, the data cover 2004 to 2011. This dataset was downloaded from the BvD proprietary online browser for Orbis data.[11] The online platform of the Orbis database provides

and was not involved in analyzing and preparing the results reported herein.

[9]The 10 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 Nielsen county size

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

[11]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.

software that automatically matches firms based on their name, address, industry code, and other information available in both Orbis data and other data. I exploit this feature to merge GS1 data and the corresponding barcode-level information with all other firm-level and bank-level information, including the FISD.[12] The FISD records historical corporate bond issuance and ratings and is used to extract information on producers' bond market access.

Finally, I combine the Dealscan database to extract information on bank lending to each producer. The Dealscan database contains comprehensive historical information on loan pricing and contracts' details, terms, and conditions. It includes mainly 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, identifying 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. The data record between one-half and three-fourths of the volume of outstanding commercial and industrial loans in the United States (Carey and Hrycay 1999).

I supplement the combined data with Zillow housing price data and Current Population Survey (CPS) data on home ownership to specifically address the drop in housing prices and home ownership 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 et al. (2016), and industry-level inventory information from the NBER-CES database (Bartelsman et al. 2000).

Table 1 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. 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 about three product groups, such as pet food or 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] While this

First, only the most recent 10 years of the sample are available on the online platform. If I had downloaded data in 2015, 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, the coverage of 2011 (and 2012) would likely be incomplete.

[12] I also hand-checked the validity of the merged sample.

[13] My sample considers more than one-fourth of sales and about one-third of the total number of purchases in the Nielsen data. Originally, there were slightly less than 20,000 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

Table 1: Summary Statistics for the Pre-Lehman Period (2005Q4-2006Q2; 2006Q4-2007Q2)

variable	**N**	**mean**	**sd**	**p10**	**p50**	**p90**
Panel A: Firm-group variables						
P_{fg}	2055	2.89	5.09	0.67	1.58	5.48
Sales (in million $)	2055	28.51	110.34	0.04	1.36	56.08
Number of UPC	2055	94.00	228.15	3	30	217
Number of buyers (in million)	2055	7.00	27.34	0.01	0.34	14.29
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 obtained loans classified as for a corporate purpose or as working capital from banks before and after the Lehman failure. All the summary statistics are based on the pre-Lehman period, 2005:Q4 to 2006:Q2 and 2006:Q4 to 2007:Q2. The variables P_{fg} (firm-group-specific price index) and demand elasticities are defined based on the nested CES demand system discussed in section 3.2. ΔL_f is the main measure of bank shock constructed from the change in loans issued by the bank. Lehman exposure is the percentage of the banks 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 3.1.

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 to credit supply shock. In addition, there remains large 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 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.

3 Empirical Analyses

Using the micro-level data discussed in the previous section, this section analyzes the effect of credit market stress on output prices and inventory dynamics. I first discuss the construction of main firm-group-specific variables, the regression specification, key identification assumptions, and the empirical results. Then, I propose an explanation for why firms facing a negative credit supply shock lower their prices, and I provide strong empirical support for the proposed mechanism. Additionally, I estimate the heterogeneous treatment effects and conduct numerous robustness checks to confirm the findings and obtain additional insights from the data.

3.1 Credit Supply Shock (ΔL_f)

I follow Chodorow-Reich (2014) to construct the ΔL_f, credit supply shock measure, which simply and coherently extracts information on changes in 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 is 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 2a). At the same time, the number and amount of loans issued plummeted, and the interest spread spiked (Figure 2b, 2c). The pre-Lehman period corresponds to the same quarters in 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.[14] However, additionally defining this period as a pre-Lehman period does not alter the result, as shown in section 3.7.1. In fact, this period provides a useful placebo setup

record balance-sheet information for these exceptionally small firms.

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

to check the validity of the measure of Lehman exposure, given the modest degree of financial market stress. In section 3.7.1, 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:

$$\Delta L_f = \sum_{b \in S_f} \alpha_{fb,\text{last}} \Delta(\text{Bank Health})_{-f,b} \tag{3.1}$$

where $\Delta(\text{Bank Health})_{-f,b}$ is a measure of the firm-bank-specific change in bank health defined below (equation 3.2), 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.[15] S_f is the set of banks that lend to firm f for the last syndicated loan 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 with 80% of its loans borrowed from Chase Bank and 20% from Citibank. Then, I used 0.8 and 0.2 as the weights to take a weighted average of changes in bank health for Chase Bank and Citibank to measure the credit supply shock faced by Smucker's. While 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 Appendix C.6. This finding is likely attributable to the stable firm-bank relationship.

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

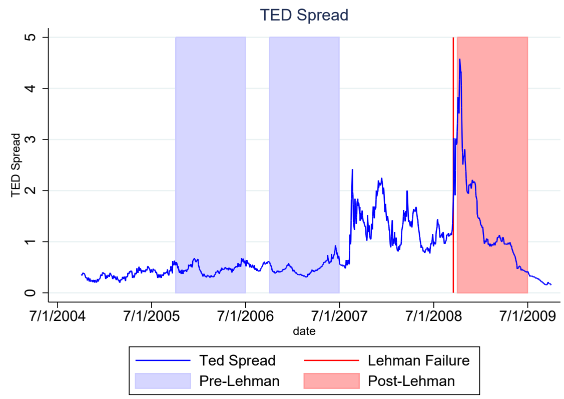
$$\Delta(\text{Bank Health})_{-f,b} = \frac{\sum_{j \neq f} \alpha_{jb,\text{post}} \times \mathbb{1}(\text{b lent to j in post-Lehman})}{\frac{1}{2}\sum_{j \neq f} \alpha_{jb,\text{pre}} \times \mathbb{1}(\text{b lent to j in pre-Lehman})} \tag{3.2}$$

where $\mathbb{1}()$ is an indicator variable equal to 1 if what is in parentheses is true and 0 otherwise, and α_{jbt} denotes bank b's share of the total amount of the loan for each syndicated loan 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.

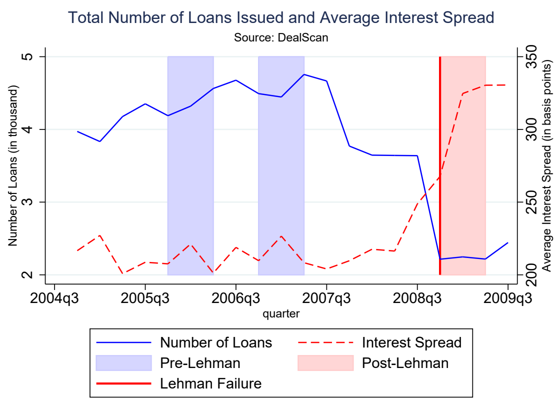
Roughly, equation (3.2) is a change in the number of loans issued by banks: the number of loans made by bank b in the post-Lehman period over the number of loans made by bank b in the pre-Lehman period. There are two additional complications. First, to reflect the importance of each loan issued by bank 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

[15] The weight reflects the fact that multiple banks arrange a loan to a firm and 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 missing α_{jbt} using the method in Chodorow-Reich (2014).

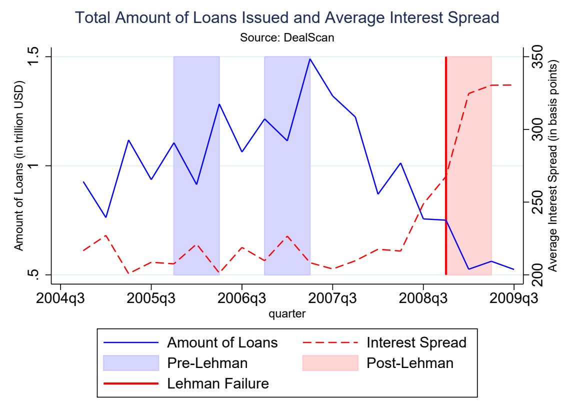
Figure 2: Timing of the Credit Supply Shock (ΔL_f)



(a) TED Spread



(b) Number of Loans and Interest Spread



(c) Amount of Loans and Interest Spread

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 the borrower pays in basis points over LIBOR for each dollar drawn down and averaged across loans within each quarter. The Lehman failure occurred in September 2008, at the end of 2008:Q3.

Smucker's and to other companies. If I use Chase Bank's loan to Smucker's to measure Chase's change in bank health, this measure might reflect the change in credit demand arising from Smucker's product market decisions or financing policies, rather than 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 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 (3.1).[16]

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 I constructed. As shown in Table 2, the credit supply shock is not correlated with purchasers' characteristics or with firms' access to the loan market, 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 unobserved firm characteristics are balanced. The details of this analysis are reported in Appendix C.8.

In addition to the measure of credit supply shock constructed above, I use three bank-level measures of the change in bank health as instrumental variables to confirm the findings. They are (i) banks' exposure to Lehman, (ii) 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 others and decrease their lending relatively more after the Lehman collapse. According to Ivashina and Scharfstein (2010), this pattern occurs because borrowers that had a credit line in which Lehman Brothers had a lead role aggressively draw down their credit lines when the lead lender becomes bankrupt because of the precautionary motive, draining the liquidity of others 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 the variation in changes in bank health due to 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 the bank's net trading revenue—where many subprime write-downs occurred—and bank deposits divided by its assets before the Lehman failure. All

[16] Note that I used a number of loans instead of an amount of loans. I do this to minimize measurement error due to the imputation of α_{fbt}. Using an amount of loans does not change the results, however, as reported in Appendix C.6. 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 the amount of loans. Loan size remained stable in this period (Darmouni 2016).

Table 2: Comparison of Pre-Lehman Observed Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(housing price)	Home ownership	ln(income)	Employment	Education	Household size
Unit	Log	%	Log	%	Years	Number
ΔL_{f}	-0.03	0.00	-0.00	0.00	-0.03	0.02
	(0.02)	(0.00)	(0.02)	(0.01)	(0.05)	(0.03)
R^2	0.01	0.01	0.00	0.00	0.00	0.00
obs	202	202	202	202	202	202
	(7)	(8)	(9)	(10)	(11)	(12)
	Number of loans	Amount of loans	Bond	List	Age	Multi-lead
Unit	Number	\$b	D	D	Years	D
ΔL_{f}	0.93	2.12	-0.08	-0.06	2.07	-0.02
	(1.16)	(2.33)	(0.06)	(0.07)	(5.53)	(0.04)
R^2	0.00	0.00	0.01	0.00	0.00	0.00
obs	206	206	206	206	204	206
	(13)	(14)	(15)	(16)	(17)	(18)
	Spread (median)	Maturity	Total assets	Employment	Inventory/asset	Cash/asset
Unit	bp	Month	\$m	k	%	%
ΔL_{f}	-14.95	1.61	7.14	73.00	-0.00	-0.02
	(23.87)	(2.40)	(7.49)	(63.16)	(0.03)	(0.02)
R^2	0.00	0.00	0.03	0.03	0.00	0.01
obs	191	203	121	109	72	73

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are heteroskedasticity-consistent. For 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. Total assets and employment are firm-level variables in Orbis averaged across 2004, 2005, and 2006. The number and amount of loans are the 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 0 otherwise.

three measures are likely to generate variation in a change in bank health for reasons that are plausibly orthogonal to a borrower's pricing decision.[17] For each bank-specific change in bank health measure, I construct a firm-level credit supply shock following equation (3.2). The correlations among these three variables are weak at the firm level in my sample, generating presumably independent variation in the producer's credit supply condition.[18]

3.2 Firm-Group Price Index (P_{fg})

I adapt the nested CES demand system in Hottman et al. (2016) to build the firm-group-specific price index from the ACNielsen Homescan Panel database to reduce the number of barcode level observations. This framework is isomorphic to the nested logit demand system in which heterogeneous consumers demand a single product in each stage (Anderson et al. 1992). There are two advantages of this framework. First, it explicitly incorporates the effect of variety and quality on output price and allows me to decompose the index into a conventional price index and a quality-variety correction term. Second, the demand structure is consistent with the model I propose in section 4. Using more conventional price indexes, such as the Laspeyres, Paasche, and Tornqvist price index does not change the results, as shown in Appendix C.7.

Consider the following Cobb-Douglas utility function

$$\ln \mathbb{U}_t = \int_{g\in\Omega} (\varphi_{gt} \ln C_{gt}) dg, \qquad \int_{g\in\Omega} \varphi_{gt} dg = 1 \tag{3.3}$$

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:

$$C_{gt} = \Big[\sum_{f\in\Omega_{gt}} (\varphi_{fgt} C_{fgt})^{\frac{\sigma_g^F-1}{\sigma_g^F}} \Big]^{\frac{\sigma_g^F}{\sigma_g^F-1}}, \qquad C_{fgt} = \Big[\sum_{u\in\Omega_{fgt}} (\varphi_{ut} C_{ut})^{\frac{\sigma_g^U-1}{\sigma_g^U}} \Big]^{\frac{\sigma_g^U}{\sigma_g^U-1}} \tag{3.4}$$

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 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 group g at time t, σ_g^F governs the elasticity of substitution across groups for each firm, and σ_g^U governs the elasticity of substitution across firms for each UPC.[19]

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

[18] Corr(Lehman, ABX)=0.04, Corr(ABX, BankItem)=0.06, Corr(Lehman, BankItem)=0.44

[19] As discussed in Hottman et al. (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

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.

The corresponding well-known exact CES price indexes are

$$P_{gt} = \left[\sum_{f \in \Omega_{gt}} \left(\frac{P_{fgt}}{\phi_{fgt}} \right)^{1-\sigma_g^F} \right]^{\frac{1}{1-\sigma_g^F}}, \quad P_{fgt} = \left[\sum_{u \in \Omega_{fgt}} \left(\frac{P_{ut}}{\phi_{ut}} \right)^{1-\sigma_g^U} \right]^{\frac{1}{1-\sigma_g^U}} \tag{3.5}$$

and the expenditure shares of products are[20]

$$S_{fgt} = \frac{\left(P_{fgt}/\varphi_{fgt}\right)^{1-\sigma_g^F}}{\sum_{k \in \Omega_{gt}} \left(P_{fgt}/\varphi_{fgt}\right)^{1-\sigma_g^F}}, \quad S_{ut} = \frac{\left(P_{ut}/\varphi_{ut}\right)^{1-\sigma_g^U}}{\sum_{k \in \Omega_{fgt}} \left(P_{ut}/\varphi_{ut}\right)^{1-\sigma_g^U}} \tag{3.6}$$

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 output price constant. If two products have the same price, but one has a larger market share, that product has a higher perceived quality.

The relative market share can be derived from equation (3.6):

$$\frac{S_{ut}^U}{\tilde{S}_{fgt}^U} = \frac{\left(P_{ut}^U/\varphi_{ut}^U\right)^{1-\sigma^U}}{\left(\tilde{P}_{ut}^U/\tilde{\varphi}_{ut}^U\right)^{1-\sigma^U}} \tag{3.7}$$

where $\tilde{S}_{fgt}^U = \left[\prod_{u \in \Omega_{fgt}^U} S_{ut}^U \right]^{\frac{1}{N_{fgt}^U}}$, the geometric average of the market share of UPCs for firm f within group g at time t. Plugging (3.7) into (3.5), one can derive the following firm-group-time price index

$$\ln P_{fgt} = \underbrace{\ln \tilde{P}_{fgt}}_{\text{Standard Index}} \underbrace{- \frac{1}{\sigma_g^U - 1} \ln \left[\sum_{u \in \Omega_{fgt}} \frac{S_{ut}}{\tilde{S}_{fgt}} \right]}_{\text{Quality/Variety Correction}} \tag{3.8}$$

---

the number of UPCs made by firm f within group g at time t.

[20] Equation 3.6 can be recovered using Shephard's lemma.

where the first term is the geometric average of UPC-level price within the firm and the group. 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).[21]

To measure the price index in equation (3.8), I use the estimated demand elasticities (σ_g^U) from Hottman et al. (2016).[22] Because t denotes a quarterly frequency, I take a geometric average across quarters within 2006:Q4-2007:Q2 (the last three quarters in the pre-Lehman period) and 2008:Q4-2009:Q2 (post-Lehman period) to make the price index comparable to the credit supply shock for regression analysis. To construct a dependent variable in the main regression analysis, I take the difference of the logged price index across pre- and post-Lehman periods.

3.3 The Effect of the Credit Crunch on the Output Price

I examine the effect of a credit supply shock on producers' output price dynamics by using the following specification:

$$\Delta \ln P_{fg} = \lambda_g + \beta \Delta L_f + \theta X_f + \varepsilon_{fg} \tag{3.9}$$

where subscript f is the firm and g is the product group or category. P_{fg} is the firm-group-specific price index I constructed from the ACNielsen barcode-level data discussed in section 3.2. ΔL_f measures the change in the firm-level credit supply as a result of the deterioration of bank health, as discussed in section 3.1. X_f includes 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 Amiti and Weinstein (forthcoming). Using different regression weights, such as the number of products that allow matching micro-level regression analysis, does not change the results, as shown in Appendix C.5. 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 firms' pricing decisions and their previous lenders' lending decisions to other borrowers. For example, the large drop in housing prices in this period

[21] 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 choose a mediocre product in the other scenario. This intuition is reflected in the share dispersion term, which measures heterogeneity in product quality.

[22] Hottman et al. (2016) apply a modification of the "identification through heterogeneity" method originally developed by Feenstra (1994) to the same data set I use in this paper. I am grateful to the authors for providing these estimates.

affected different consumers differentially (Mian et al. 2013). Thus, these consumers potentially purchase products differentially across products made by different firms, and, in turn, these firms would likely demand a different number of loans from their lenders differentially. If these firms are large enough for the lender to cut its lending to other borrowers, 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 bank liability structure (Fahlenbrach et al. 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 in the sample, where purchasers did not tend to change their purchasing behavior, unlike those in other sectors. The empirical pattern of 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 2b, 2c). 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 issuance for each firm. The fixed effects of firms' four-digit NAICS industry and listed status, as well as 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 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 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 home ownership at the country level from the Census data. Adding these purchasers' characteristics does not change the results, as shown in Appendix C.3. Note that the observed pre-Lehman borrower and purchaser characteristics are balanced as well as shown in Table 2.

Moreover, to confirm my findings, I use three instruments that are not highly correlated but that generate plausibly exogenous variation in firms' credit supply conditions: Lehman exposure, ABX securities exposure, and bank statement items. These measures are used as instrumental variables to interpret the coefficients consistently. Using the cross-sectional variation in Lehman

Table 3: First-Stage Regression

	(1)	(2)	(3)
		ΔL_{f}	
Lehman exposure	-0.349***		
	(0.084)		
ABX exposure		-0.269***	
		(0.089)	
Bank items			0.436***
			(0.121)
Firm-level controls	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes
F statistics	17.3	9.0	12.9
$E[\Delta L$: $\mathrm{IV}_{\mathrm{p90}}$-$\mathrm{IV}_{\mathrm{p10}}]$	-.24	-.371	.495
Observations	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, 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 $\Delta \ln \mathrm{P}_{\mathrm{fg}}$

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 2016). Before its failure, Lehman was the fourth-largest investment bank and had more than $600 billion in assets, and it collapse was surprising and dramatic. By using this instrument, I effectively assume that what happened to companies in the consumer packaged goods market, such as Smucker's, 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 (sum of bank deposits and net trading revenue to assets) also generates credit-supply variation that is plausibly uncorrelated with factors that affect companies' pricing decisions. 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. The first-stage regression for each of the three instruments is reported in Table 3.

The other assumption of the regression analysis is the long-run firm-bank relationship or the existence of switching costs for companies to 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 adverse selection for switchers that prevents lenders from providing new loans. Additionally, monitoring cost is likely to decline more for repeated borrowers, easing the moral hazard problem for lenders as well. 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. Moreover, I examine a period of credit market disruption, when banks are especially hesitant to form new relationships.[23]

Table 4 shows the empirical results based on equation (3.9). I change the sign of ΔL_f to interpret β as a result of a *negative* credit supply shock on output prices. Regardless of using OLS with the main credit supply shock variable or of which instruments used, the estimated coefficients are negative, statistically significant at the 5% level, and quantitatively similar. I standardize the credit supply shock measure (ΔL_f) to interpret the coefficient. A-one-standard-deviation increase in negative credit supply shock decreases output prices 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.[24]

I confirm the empirical results by checking the pre-trend 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. The main assumption is that there are no unobserved firm-level characteristics that are simultaneously correlated with their pricing decisions and the constructed credit supply shock. One way to validate this assumption is to examine how firms that faced a negative credit supply shock set their output prices before the credit supply shock was realized. The results would be worrisome if firms that faced negative credit supply shocks changed their output prices before the shock occurred. As shown in Table 5, the estimated effect of credit supply shock on output prices in the previous period is not statistically significant regardless of which credit supply shock is used. The results are fully consistent with Figure 1c, where I plot aggregate price indexes for two groups of firm—with one facing a larger negative credit supply shock than the other—based on the main measure constructed in equation 3.2. Without conditioning on observed firm-level characteristics, two aggregate price indexes follow each other carefully but diverge sharply after the credit supply shock is realized. The regression results confirm that this pattern is robust to the inclusion of firm-level control variables and to the use of three other credit supply shock measures.

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:

[23] Empirically, Chodorow-Reich (2014) confirm this "sticky" firm–bank relationship with the regression analysis.

[24] Excluding control variables, I obtain the same qualitative results but a smaller magnitude of coefficients. The change in magnitude of the coefficients is driven mostly by the product-group fixed effects and NAICS four-digit fixed effects, highlighting the importance of comparing products in the same groups and comparing firms selling the same primary product industry code.

Table 4: Main Results

	(1)	(2)	(3)	(4)	(5)
	$\Delta\ln\mathrm{P}_{\mathrm{fg}}$: 2006q4-2007q2 to 2008q4-2009q2				
	OLS	($-\Delta L_f$) instrumented using			
		Lehman	ABX	BankItem	All
($-\Delta L_f$)	-8.43***	-7.83**	-6.79**	-8.23**	-7.76***
	(1.53)	(3.56)	(3.05)	(3.13)	(2.26)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes	Yes
First-stage F statistics		17.3	9.0	12.9	10.8
J-statistics p-value					0.92
$E[\Delta\ln\mathrm{P}]$	11.4	11.4	11.4	11.4	11.4
$E[\Delta\ln\mathrm{P}$:($-\Delta L_{\mathrm{p90}}$)-($-\Delta L_{\mathrm{p10}}$)]	-18.4	-17.1	-14.8	-17.9	-16.9
Observations	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, 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 $\Delta\ln\mathrm{P}_{\mathrm{fg}}$

Table 5: Pretreatment Trends Regression

	(1)	(2)	(3)	(4)	(5)
	$\Delta\ln\mathrm{P}_{\mathrm{fg}}$: 2004q4-2005q2 to 2006q4-2007q2				
	OLS	($-\Delta L_f$) instrumented using			
		Lehman	ABX	BankItem	All
($-\Delta L_{\mathrm{f}}$)	-3.5	1.8	-6.4	-6.6	-4.1
	(2.9)	(4.5)	(4.7)	(5.2)	(3.6)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes	Yes
First-stage F statistics		16.8	9.2	13.1	10.8
J-statistics p-value					0.21
$E[\Delta\ln\mathrm{P}]$	4.9	4.9	4.9	4.9	4.9
$E[\Delta\ln\mathrm{P}$:ΔL_{p90}-ΔL_{p10}]	-7.7	4	-14.2	-14.7	-9
Observations	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, 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 post-Lehman FE, loan spread, and loan maturity

$$\ln P_{fg,t} - \ln P_{fg,t-4} = \lambda_g + \beta_t(\text{-}\Delta L_f) + \theta X_f + \varepsilon_{fg} \tag{3.10}$$

where t is the quarter, not the pre- and post-Lehman periods. (-ΔL_f) is the measure of Lehman exposure directly used in the regression as a reduced-form, rather than instrumenting the main measure.[25] Based on this regression analysis, I estimate the effect of a credit supply shock for all quarters in the data.

The estimated coefficients are plotted in Figure 3. Although there is more noise in the data compared to the main regression analysis (Table 4) because of the quarterly frequency, the figure reveals the clear dynamic effect of the bank shock on output price dynamics. The estimated coefficients are not statistically different from 0 before the Lehman failure, suggesting that there is no pre-trend. At the time of the Lehman failure, however, coefficients are negative for the first two quarters and near 0 for the subsequent quarters, showing that firms facing a negative credit supply shock decreased their output prices. After a year, however, the estimated coefficients become positive for approximately three quarters and then are 0 for the remaining quarters. This plot clarifies that the effect is temporary and that firms increase their output prices in the medium run and long run. The fire sale of inventory hypothesis is fully consistent with this effect. If it is true that firms decrease their output prices by liquidating inventory and dumping their products on the market, they would not be able to sell their inventories forever, and thus, they must accumulate inventory at some point, suggesting that the effect should be temporary. I discuss this hypothesis in detail in the next section.

3.4 Mechanism: Fire Sale of Inventory

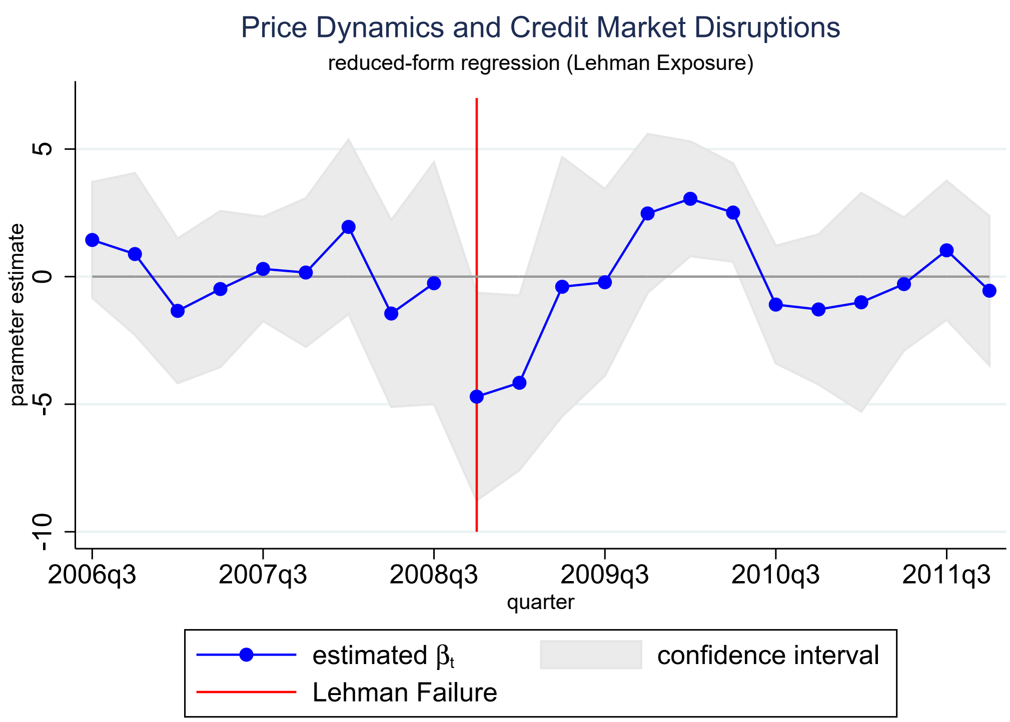
The result in the previous section seems counterintuitive, as most studies think of financial distress as an increase in credit cost and hence predict an increase in prices due to a negative credit supply shock.[26]

I propose a hypothesis that can rationalize the empirical finding; what I call 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, firms that cannot borrow from their lenders try to accumulate cash by selling off their inventory at low prices to generate extra cash flow. At the aggregate level, inventory holdings decreased dramatically after the Lehman failure (Figure 1d), suggesting that the hypothesis I propose is plausible, at least an aggregate level. I then return to the micro-level

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

[26] Papers that emphasize the effect of financial cost on output price include Del Negro et al. (2015), Christiano et al. (2015), and Barth and Ramey (2002). 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 the financial friction.

Figure 3: Result: Dynamics



Note. This figure is based on equation (3.10), $\ln P_{fg,t} - \ln P_{fg,t-4} = \lambda_g + \beta_t(\text{-}\Delta L_f) + \theta X_f + \varepsilon_{fg}$. 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; the regression is weighted by initial sales; and firm-level controls are the firm's listed status, 4-digit NAICS FE, age, size, 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 data and the corresponding identification strategy used to study firms' pricing behavior to support the proposed mechanism.

I use the following regression specification:

$$\Delta Y_{fg} = \lambda_g + \gamma(\text{-}\Delta L_f) + \theta X_f + \varepsilon_{fg} \tag{3.11}$$

where ΔY_{fg} equals four dependent variables: change in inventory, market share, cash holding, and employment.[27] Note that the market share is the only firm-group specific variable among the four dependent variables, and product-group fixed effects are not allowed in the regression for other variables. ΔL_f is the credit supply shock constructed in section 3.1, and X_f is the corresponding firm-level control variable.

I provide strong empirical support for the fire sale of inventory hypothesis, as shown in Table 6. I observe inventory holding at the firm-level and directly test this hypothesis. I find that firms facing a negative credit supply shock liquidate their inventories. Additionally, those firms increase their market share, suggesting that they increase their sales by selling more of their products, and they accumulate more cash, suggesting that these firms generate extra cash flow from the product market by selling off their inventory. I also find that these firms lay off workers, which is a well-known result from the literature. Note that firms that face a negative credit supply shock can increase sales even they decrease production (or employment) because they draw down their inventories to generate extra cash flow from the product market. I report only the regression results instrumented with the measure of Lehman exposure, but the results are consistent if I use other credit supply shock measures.

3.5 Heterogeneous Treatment Effect

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

$$\Delta \ln P_{fg} = \lambda_g + \beta(\text{-}\Delta L_f) \times Z_{fg} + \theta X_f + \varepsilon_{fg} \tag{3.12}$$

where Z_{fg} represents the firm- or group-level characteristics before the year 2007, such as cash or inventory holdings. The only difference between this specification and equation (3.9) 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 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

[27](1) Inventory$_f$: $\frac{\text{Inv}_{f,2008}-\text{Inv}_{f,2006}}{\text{Inv}_{f,2006}}$, (2) Market Share$_{fg}$: $\left(\frac{\text{sales}_{fg}}{\text{sales}_g}\right)_{2008q4\text{-}2009q2} - \left(\frac{\text{sales}_{fg}}{\text{sales}_g}\right)_{2006q4\text{-}2007q2}$, (3) Cash Holding$_f$: $\left(\frac{\text{cash}}{\text{total asset}}\right)_{f,2008} - \left(\frac{\text{cash}}{\text{total asset}}\right)_{f,2006}$, (4) Employment: $\frac{\text{Emp}_{f,2008}-\text{Emp}_{f,2006}}{\frac{1}{2}(\text{Emp}_{f,2006}+\text{Emp}_{f,2008})}$.

Table 6: Fire Sale of Inventory Hypothesis

Y_{fg}	(1) Inventory$_f$	(2) Market Share$_{fg}$	(3) Cash Holding$_f$	(4) Employment$_f$
(-ΔL_f) instrumented using Lehman	-21.1***	2.42**	5.6***	-13.9***
	(7.3)	(1.18)	(1.7)	(6.7)
Firm-level controls	Yes	Yes	Yes	Yes
Product group FE	No	Yes	No	No
First-stage F statistics	61.0	18.9	38.2	66.7
$E[\Delta \ln \mathrm{Y}$:(-ΔL_{p90})-(-ΔL_{p10})]	-50	5.3	13.2	-36
Observations	958	1658	1210	1011

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by firm and product group for market share and by three-digit NAICS for the other three dependent variables; the regression is weighted by initial Y_{fg}; and firm-level controls are the 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, size, and bond rating.

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. Equation (3.12) is used throughout this section.

I first use the variation in initial cash holdings to find that cash-poor firms—companies with a small amount of cash in the pre-Lehman period—decrease their output prices more than their counterparts when they face a negative bank shock, as shown in Table 7. This analysis supports the notion that firms sell off inventory to ensure their liquidity when they face an exogenous increase in the cost of external finance. 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, 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. Firms that lack internal liquidity, however, are more likely to sell their inventories and decrease their output prices to ensure extra funds. The results additionally highlight the importance of cash in managing corporations' liquidity.

I utilize numerous other firm-level characteristics to confirm the empirical findings and to understand which types of firms are most likely to decrease their prices because of the negative credit supply shock, as shown in Table 8. According to the fire sale of inventory hypothesis, firms that had a lot of inventory before the Lehman failure should drop their prices more aggressively than firms with small initial inventory because they have more inventory to sell. I test this prediction by using the variation in the initial inventory holdings and find that the effect is indeed stronger for firms with large initial inventory. The key assumption in this regression that firms did not store inventory in preparation for the credit crunch is supported in Table 2 and consistent with the model in section 4, where producers hold inventories to avoid the stock-out of products.

Table 7: Treatment Interaction: Initial Cash Holding

	$\Delta\text{lnP}_{\text{fg}}$: 2006q4-2007q2 to 2008q4-2009q2			
	(1)	(2)	(3)	(4)
L_f	#Lending	Lehman	ABX	BankItem
$\left(-\frac{\text{cash}}{\text{total asset}}\right)_{f,2006} \times (-\Delta L_f)$	-5.14**	-26.21***	-11.67**	-3.86***
	(2.09)	(5.62)	(5.10)	(0.73)
$(-\Delta L_f)$	-7.73	7.35***	-8.24***	-9.53***
	(5.44)	(1.88)	(2.56)	(1.24)
Firm-level controls	Yes	Yes	Yes	Yes
Observations	832	832	832	832

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, 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 measures of Lehman exposure, ABX securities exposure, and bank items are used as direct measures of credit supply shock, not as instruments.

Given that the assumption is more plausible at the industry level, I also use industry-level initial inventory variation to confirm this finding. Additionally, the effect is stronger for firms that borrowed a higher loans amount immediately before the Lehman failure and weaker for firms that issued a bond or had multiple lead lenders in the pre-Lehman period. These results show that the bank shock is more damaging for companies that heavily rely on shocked banks but less damaging for companies that can rely on an alternative source of financing or alternative banks. Additionally, the effect is larger for companies that had more loans that matured in the post-Lehman period. Given that the Lehman failure was a surprise, firms that had to pay out their debts are likely to suffer more financial problems from the credit crunch and decrease their prices more to liquidate inventories and generate extra liquidity. Moreover, the effect is stronger for firms that had smaller total assets and fewer employees, consistent with studies that find that the effect of credit supply shock is larger for small companies (e.g., Duygan-Bump et al. 2015).

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 firms that face high demand elasticity, as shown in Table 9. Allowing firm fixed effects does not alter this result, suggesting 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.[28] The estimated elasticities in the regression analysis are based on

[28] Of course, such firms might have less incentive to lower their prices. If firms facing a negative bank shock target a particular amount of sales, firms facing inelastic demand might have a stronger incentive to lower their prices. However, reduced-form empirical analysis does not support this prediction.

Table 8: Treatment Interaction: Firm-level Characteristics

	(1)	(2)	(3)	(4)
	$\Delta \mathrm{lnP_{fg}}$: 2006q4-2007q2 to 2008q4-2009q2			
$(-\Delta L_f) \times \mathrm{inven_{f,2006}}$	-8.35***			
	(1.04)			
$(-\Delta L_f) \times$ industry inven_f		-11.49**		
		(4.93)		
$(-\Delta L_f) \times$ loan $\mathrm{amount_f}$			-2.69**	
			(1.20)	
$(-\Delta L_f) \times$ loan $\mathrm{due_f}$				-9.56**
				(4.27)
$(-\Delta L_f)$	95.37***	59.97*	44.72*	-4.98***
	(11.19)	(31.32)	(23.60)	(1.70)
Firm-level controls	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes
Observations	832	496	1844	1844
	(5)	(6)	(7)	(8)
	$\Delta \mathrm{lnP_{fg}}$: 2006q4-2007q2 to 2008q4-2009q2			
$(-\Delta L_f) \times$ bond $\mathrm{access_f}$	5.81**			
	(2.54)			
$(-\Delta L_f) \times$ multi-$\mathrm{lead_f}$		1.63*		
		(0.94)		
$(-\Delta L_f) \times$ total $\mathrm{asset_f}$			10.73***	
			(2.47)	
$(-\Delta L_f) \times \mathrm{employment_f}$				7.69***
				(1.34)
$(-\Delta L_f)$	-4.98***	-8.75**	-163.75***	-75.85***
	(1.66)	(3.61)	(37.71)	(12.60)
Firm-level controls	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes
Observations	1800	1800	834	834

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, four-digit NAICS FE, 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; inven_f: firm-level 2006 ln(inventory); industry inven: NAICS four-digit 2001-2006 average ln(inventory); loan amount_f: last pre-Lehman ln(loan amount) the nested CES demand system in section 3.2, and the results are robust to different market structure assumptions. The derivation of demand elasticity under different market structure assumptions are in Appendix A of Hottman et al. (2016).[29]

3.6 Additional Empirical Analyses

This section presents three additional empirical analyses. First, I discuss how my empirical results are related to Gilchrist et al. (2017), who find that firms in a weak liquidity position increase their output prices. Second, I utilize the nested CES demand system to decompose the price index into a conventional price index and a variety-quality adjustment and find that all of the effect of a negative credit supply shock works through the conventional price index, not through a change in the quality or variety of products. Finally, I check and confirm the external validity of the empirical results by using more-representative data with a different period and identification strategy.

3.6.1 Reconciliation with Gilchrist et al. (2017)

The results in this paper appear to oppose those in Gilchrist et al. (2017), who, based on their empirical findings, conclude that financially constrained firms raise their output prices relative to their counterparts. I argue that my empirical results, in fact, are fully consistent with their results that firms in a "weak liquidity position" raise their output prices. The difference between these two studies lies in the interpretation of the results.

I first replicate and confirm their results in my sample with their measure of financial constraint, a small amount of cash holdings, using the following regression specification.

$$\Delta \ln P_{fg} = \lambda_g + \gamma \mathrm{LIQ}_f + \theta X_f + \varepsilon_{fg} \tag{3.13}$$

where LIQ_f stands for liquidity, which is either initial (2006) cash to assets or contemporaneous (2008) cash to assets. As reported in Table 10, even in my sample, firms that had a small amount of cash at the beginning or during the banking crisis raised their output prices relative to their counterparts. The natural question that arises is why different measures of financial constraint, liquidity and bank shock, generate different results.

Previous studies in the corporate finance literature suggest that firms in a "weak liquidity position" are likely to be *less* financially constrained, not more financially constrained. A large body of literature asks why firms hold liquidity. Almeida et al. (2014) survey this literature and conclude that the main cause of cross-sectional variation in liquidity position is financial constraint. That is, companies that hold liquidity are likely to be more financially constrained, not less financially constrained.

[29] 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.

Table 9: Treatment Interaction: Demand Elasticity

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \ln P_{fg}$: 2006q4-2007q2 to 2008q4-2009q2					
$(-\Delta L_f) \times$ demand elasticity$_{fg}$ (Bertrand)	-2.19***	-1.74**				
	(0.67)	(0.73)				
$(-\Delta L_f) \times$ demand elasticity$_{fg}$ (Cournot)			-2.26***	-2.15**		
			(0.81)	(0.86)		
$(-\Delta L_f) \times$ demand elasticity$_{g}$ (UPC)					-0.59**	
					(0.24)	
$(-\Delta L_f) \times$ demand elasticity$_{g}$ (Firm)						-1.49***
						(0.53)
$(-\Delta L_f)$	4.61**		3.37		1.66	3.28
	(2.30)		(2.38)		(2.00)	(2.36)
demand elasticity$_{fg}$ (Bertrand)	-1.71*	-1.00				
	(0.89)	(1.10)				
demand elasticity$_{fg}$ (Cournot)			-1.43*	-0.49		
			(0.73)	(0.87)		
Firm-level controls	Yes	No	Yes	No	Yes	Yes
Firm FE	No	Yes	No	Yes	No	No
Product group FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1811	1811	1811	1811	1811	1811

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; firm-level controls are the firm's listed status, firm age, two-digit NAICS FE, 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; and the number of UPC$_g$ is the number of UPCs in each group, and number of buyers$_g$ is the number of buyers in each group.

Table 10: Effect of Corporate Cash Holding on the Output Price

	(1)	(2)	(3)	(4)
	$\Delta\ln\mathrm{P}_{\mathrm{fg}}$: 2006q4-2007q2 to 2008q4-2009q2			
	LIQ_f is $-\left(\frac{\text{cash}}{\text{total asset}}\right)_{2008}$		LIQ_f is $-\left(\frac{\text{cash}}{\text{total asset}}\right)_{2006}$	
LIQ_f	8.84***	4.59**	9.08***	5.96**
	(1.96)	(2.10)	(2.42)	(2.88)
Four-digit naics FE	No	Yes	No	Yes
Product group FE	No	Yes	No	Yes
$E[\Delta\ln\mathrm{P}]$	9.5	9.5	9.5	9.5
$E[\Delta\ln\mathrm{P}{:}\Delta L_{\mathrm{p90}}\text{-}\Delta L_{\mathrm{p10}}]$	5.48	2.85	7.38	4.84
Observations	1461	1454	1524	1515

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by firm and product group. LIQ_f is normalized to have a unit variance.

More specifically, consider the contemporaneous (2008) liquidity position. Kahle and Stulz (2013) find that 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 companies facing a negative credit supply shock raise their liquidity, as shown in Table 6. This result is consistent with the fire sale of inventory hypothesis, reflecting that such firms want to sell their inventory to hold more liquidity due to the precautionary motive. However, such companies facing 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 initial (2006) liquidity position, a seminal work by Bates et al. (2009) identifies more than 10 factors that lead firms to hold more liquid assets. In particular, they find that the "weak liquidity position" is associated with more investment, borrowing, and acquisitions, and stable cash flow, characteristics that likely reflect unconstrained companies rather than constrained companies. I confirm the findings of Bates et al. (2009) using liquidity position for the year 2006 only as shown in Appendix D. Firms that had a small amount of liquidity in 2006, in fact, invest more, borrow more, acquire more firms, and had stable cash flow in 2006 and 2008. Because of these concerns of using the "weak liquidity position" as a measure of financial constraint, I instead use the bank shocks proposed by Ivashina and Scharfstein (2010) and Chodorow-Reich (2014), which are not subject to this criticism. Moreover, I find that my results are robust to the inclusion of the initial cash holdings in the regression. See Appendix D for more detailed discussion.

3.6.2 Price Adjustment vs. Quality-Variety Adjustment

One of the most important aspects of studying price dynamics is the effect of changes in variety and quality on the output price index. The firm-group level price index—or the cost-of-living index—depends crucially on how many products are available in the market and how appealing each product is to purchasers. The nested CES demand system used in this article has an advantage over other conventional price indexes, such as the Tornqvist or Laspeyres indexes, because it explicitly incorporates the utility gains from the products' greater variety and high quality into the price index. The analysis so far, however, does not reveal how large this effect of variety and quality adjustment is on the output price index due to the negative credit supply shock. Firms that face a negative credit supply shock decrease their output price index by increasing the number of products by drawing down inventories of new products or by downgrading product quality to reduce costs rather than decreasing their actual product prices.

I decompose the price index into the conventional price index and the quality-variety correction and find that all the effects of the credit supply shock work through the conventional price index rather than through quality or variety adjustment. As discussed in section 3.2, the nested CES demand system allows the price index to be decomposed into a conventional price index and the variety-quality correction term. I regress each part of the price index on the credit supply shock measure and report the results in Table 11. The coefficients are negative and statistically significant when the conventional price index is used, but they are close to 0 and not statistically significant when the quality-variety correction part of the price index is used. This result suggests that firms that face negative credit supply shocks do not alter the variety or quality of their products to change their output price index but instead simply decrease the prices of their products. Based on this result, I abstract away from firms' product entry and exit decisions and product quality decisions to construct the business cycle model presented in section 4.

3.6.3 External Validity

A potential concern in this study is the generality of the main empirical result. I consider only the period around the Lehman bankruptcy, and while this timing has an advantage over other periods in identifying the effect of credit supply shock because of the surprising nature and enormous magnitude of the credit market disruptions in this period, it limits the scope of the study. In particular, given that Lehman failed during the middle of the Great Recession, the results can speak only to the recession period, when other fundamental variables were likely to change simultaneously.[30] Additionally, my data cover products that have a barcode and that are typically purchased at grocery stores. Studying this consumer packaged goods market is again useful in addressing the internal validity problem. This market is likely to be the least sensitive to other potential confounding factors, such as product demand shock, compared with industries with more durable or demand-elastic products. However, a study based on this dataset would not provide information on other industries and is unlikely to be fully representative despite its

[30] For example, Stroebel and Vavra (2016) suggest that demand becomes more elastic during the recession. In this case, credit-constrained firms would be more likely to decrease their output prices in the recession than in the boom, as firms are more likely to generate larger cash flows from decreasing output prices when they face elastic demand, as shown in Table 9.

Table 11: Effect of the Credit Crunch on the Output Price: Decomposition

	(1)	(2)	(3)	(4)	(5)
	$\Delta\ln\tilde{P}_{\text{fg}}$: 2006q4-2007q2 to 2008q4-2009q2				
	OLS	$(-\Delta L_f)$ instrumented using			
		Lehman	ABX	BankItem	All
$(-\Delta L_f)$	-8.24***	-7.85*	-7.34**	-6.95*	-7.32***
	(1.90)	(4.11)	(3.27)	(3.69)	(2.43)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes	Yes
First-stage F statistics		17.2	9.1	13.0	10.9
J-statistics p-value					0.98
$E[\Delta\text{lnP}]$	11.4	11.4	11.4	11.4	11.4
$E[\Delta\text{lnP}{:}(-\Delta L_{\text{p90}})\text{-}(-\Delta L_{\text{p10}})]$	-18	-17.1	-16	-15.2	-16
Observations	1658	1658	1658	1658	1658

	(7)	(8)	(9)	(10)	(11)	(12)
	$\Delta\ln SD_{\text{fg}}$: 2006q4-2007q2 to 2008q4-2009q2					
	OLS	$(-\Delta L_f)$ instrumented using				
		Lehman	ABX	BankItem	All	
$(-\Delta L_f)$	-0.02	0.46	0.46	-1.00	-0.20	
	(0.80)	(1.38)	(1.02)	(1.19)	(0.74)	
Firm-level controls	Yes	Yes	Yes	Yes	Yes	
Product group FE	Yes	Yes	Yes	Yes	Yes	
First-stage F statistics		16.9	9.2	12.8	10.9	
J-statistics p-value					0.54	
$E[\Delta\text{lnP}]$	0	0	0	0	0	
$E[\Delta\text{lnP}{:}(-\Delta L_{\text{p90}})\text{-}(-\Delta L_{\text{p10}})]$	0	1	1	-2.2	-.4	
Observations	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, 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 dependent variable non-negligible share of total consumer expenditure.

To address external validity concerns, I confirm the main empirical finding with a different identification strategy in a different period with more-representative data. First, I gather BLS monthly NAICS four-digit industry-level price data from December 1984 to December 1996 for manufacturing sectors, build a Rajan and Zingales (1998) external financial dependence index at the NAICS four-digit industry-level from the Compustat database, and collect monthly Fed funds rate shocks from Romer and Romer (2004). With these measures, I examine how industries that rely heavily on external finance change their output prices relative to their counterparts when there is an exogenous increase in the Fed funds rate. This analysis relies on the notion of the cost channel of monetary policy. The exogenous increase in the Fed funds rate affects credit spread firms borrowing from financial intermediaries, and firms that operate in external-finance-dependent industries should face a larger negative credit supply shock than their counterparts. Based on this variation in the data, I evaluate the main empirical findings in a more general setup.

I use the following specification:

$$\Delta \ln P_{jt} = \lambda_j + \lambda_t + \delta(\mathrm{RZ}_j \times \Delta ff_t) + \theta X_{jt} + \varepsilon_{jt} \tag{3.14}$$

where j is the NAICS four-digit industry code, t is the month. P_{jt} is the BLS industry-level monthly price index, RZ_j is the industry-specific Rajan-Zingales external financial dependent index, Δff_t is the monthly Fed-funds rate shock, X_{jt} represents industry-level control variables, and λ_j and λ_t are industry and time fixed effects, respectively, including (NAICS 2-digit)$\times\Delta ff_t$, (Durability Index)$\times\Delta ff_t$, (Luxuriousness Index)$\times\Delta ff_t$, and $\mathrm{RZ}_j\times$(Month Dummies)$_t$. The Luxuriousness Index and Durability Index come from Bils et al. (2013) and measure product luxuriousness and durability for each industry, respectively. The coefficient δ measures the effect of the credit supply shock on industries dependent on external finance.

I find that external-finance-dependent industries reduce their output prices because of the exogenous increase in the Fed funds rate relative to their counterparts, as reported in column (1) of Table 12. These results help ensure that firms that face negative credit supply shocks decrease their output prices in other periods based on all manufacturing data. To additionally check whether the results are generated by the recession period in 1990, I follow the NBER definition of a recession to make a dummy variable that equals 1 for the period from July 1990 to March 1991 and 0 otherwise. Then, I interact this variable with the shock variables, but I find no evidence that the effect is larger for the recession period. Additionally, the results are robust when this recession period is excluded from the sample, suggesting that the effect exists at normal times. Finally, I added a lagged monetary policy shock interacted with the financial dependent index, and I find no effect based on this lagged shock variable. These results suggest that the effect is temporary, consistent with the fire sale of inventory hypothesis.

Table 12: Effect of the Credit Crunch on the Output Price: External Validity

Dependent Variable:	$\Delta \ln P_{jt}$			
	(1)	(2)	(3)	(4)
$\mathrm{RZ}_j \times \Delta ff_t$	-0.172**	-0.166**	-0.155*	-0.173**
	(0.075)	(0.079)	(0.079)	(0.076)
$\mathrm{D}_{\mathrm{recession}} \times \mathrm{RZ}_j$			-0.000	
			(0.000)	
$\mathrm{D}_{\mathrm{recession}} \times \mathrm{RZ}_j \times \Delta ff_{t-1}$			-0.269	
			(0.253)	
$\mathrm{RZ}_j \times \Delta ff_{t-1}$				0.032
				(0.052)
Observations	3467	3251	3467	3464
R^2	0.077	0.083	0.077	0.077
Industry and time FE	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes
Exclude recession?	No	Yes	No	No

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by month and corrected for the autocorrelation following Driscoll and Kray (1998); control variables are (NAICS 2-digit)$\times\Delta ff_t$; (Durability)$\times\Delta ff_t$; (Luxuriousness Index)$\times\Delta ff_t$; $\mathrm{RZ}_j\times$(Month Dummies)$_t$

Figure 4: Inflation and Bank Crisis: External Validity

Note. All the above panels show the average inflation and real GDP for the five years around the peak of the crisis year. In the upper panels, the figure compares banking and non-banking crises in 14 developed countries for which data are available, and does so for the United States only in the lower panels. The 14 developed countries are the United States, Canada, Australia, Denmark, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom. There are 79 banking crises (7 for the United States) from 1870 to 2008 (Schularick and Taylor 2012), and 47 other crises (6 for the United States) from 1950 to 2006 (Ottonello 2015).

In addition, I divide all the recessions that occured in 14 developed countries into banking crises, as defined in Schularick and Taylor (2012), and nonbanking crises, as defined in Ottonello (2015). I then take a simple average of inflation and employment across recessions and countries within the type of crisis for each of the five years around the year of recession and then plot the results in Figure 4. As shown in the figure, inflation seems to fall in banking crises but rise in nonbanking crises, despite a large decrease in real GDP, consistent with the empirical findings in this article. This result is robust when I look only at the United States. Note that the magnitude of change in inflation in banking crises is quite different from that for nonbanking crises, as the data had more historical information for banking crises, when the average inflation was lower than in recent periods. Dropping recession years before 1950 generates a similar magnitude of average inflation as that in nonbanking crises, from 5 to 8 percent for all 14 countries.

In Appendix C, I conduct numerous robustness checks to address potential concerns related to the timing of the credit supply shock, retailers' behavior, local conditions, and purchaser characteristics. I also check that results are robust to the inclusion of variables related to foreign exposure and to the use of different price indexes and regression weights. I re-confirm the empirical findings by showing that none of these analyses alters the main empirical result that firms facing a negative credit supply shock decrease their output prices.

4 Theoretical Analyses

I present a business cycle model based on micro-level empirical evidence in order to shed light on aggregate inflation and inventory dynamics. I first present a simple model with two identical producers with matched micro-level data to formalize the mechanism. I then extend the model to examine the dynamics of aggregate inflation and inventory. The model is particularly related to Iacoviello (2005) and Wen (2011).

4.1 Simple Model

There are three types of agents in this model: households and two otherwise identical representative entrepreneurs facing different degrees of credit supply shock. Two identical entrepreneurs are included in order to expressly reflect a micro-level analysis of the differential change in variables. Entrepreneurs face the borrowing capability that is exogenously given to them. The thought experiment is a sudden decrease in a representative entrepreneur's borrowing capacity to determine how the output price, sale, inventory, and employment dynamics evolve compared to the other.

To integrate the fire sale of inventory hypothesis, I adapt the product stock-out motive of inventory holding, as described in Wen (2011). 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 the incentive to store products in inventory to avoid product stock-out. Introducing multiple products with idiosyncratic shock makes an inventory positive at the steady state and makes it easy to apply the conventional log linearization technique to solve the model. Moreover, this formulation allows the introduction of capital, another form of saving, without inducing firms to hold capital over inventory. Inventory yields a liquidity premium to facilitate sales, giving companies an incentive to hold both inventory and capital. This feature is useful in the extended model, in which entrepreneurs invest in capital.

4.1.1 Households

The household sector is standard. Households maximize a lifetime utility function given by

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{(c_t^H)^{1-\sigma_c}}{1-\sigma_c} - \frac{(l_t^H)^{1+\sigma_l}}{1+\sigma_l} \right]$$

where E_0 is the expectation operator, $\beta \in (0,1)$ is the discount factor, c_t^H is consumption at time t, and l_t^H is hours of work households supply for entrepreneurs. Denote $w_t \equiv W_t/P_t$ the real wage. Assume that households lend in real terms $-b_t^H$ and receive $-R_{t-1}b_{t-1}^H$, where R_{t-1} is the interest rate on loans between $t-1$ and t. The flow budget constraint is

$$c_t^H + R_{t-1}b_{t-1}^H = b_t^H + w_t l_t^H \tag{4.1}$$

The composite consumption of good in expression (1) is an index given by

$$c_t^H = \left[(c_{1t}^H)^{\frac{\eta-1}{\eta}} + (c_{2t}^H)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}$$

where c_{1t}^H is produced by entrepreneur 1 and consumed by households, and c_{2t}^H is produced by entrepreneur 2 and consumed by households. The corresponding price index is given by

$$1 = [p_{1t}^{1-\eta} + p_{2t}^{1-\eta}]^{\frac{1}{1-\eta}}$$

where p_{1t} is the price of good 1 and p_{1t} is the price of good 2. The aggregate price index is normalized to 1. Solving the above household problem yields the following first-order conditions for the aggregate consumption (4.2), labor supply (4.3), and consumption of goods 1 and 2 (4.4, 4.5):

$$\frac{1}{(c_t^H)^{\sigma_c}} = \beta E_t \left[\frac{R_t}{(c_{t+1}^H)^{\sigma_c}} \right] \tag{4.2}$$

$$w_t = (l_t^H)^{\sigma_l} (c_t^H)^{\sigma_c} \tag{4.3}$$

$$c_{1t}^H = \left(\frac{p_{1t}}{p_t} \right)^{-\eta} c_t^H \tag{4.4}$$

$$c_{2t}^H = \left(\frac{p_{2t}}{p_t} \right)^{-\eta} c_t^H \tag{4.5}$$

4.1.2 Entrepreneurs

There are two representative entrepreneurs, and they are identical except that one experiences a decrease in the borrowing constraint. They (j=1,2) maximize the following lifetime utility:

$$E_0 \sum_{t=0}^{\infty} \gamma^t \frac{(c_t^{Ej})^{1-\sigma_c}}{1-\sigma_c}$$

where c_t^{Ej} is the aggregate consumption of type j entrepreneurs at time t, and γ is the discount factor for entrepreneurs. I assume entrepreneurs are more impatient than households ($\gamma < \beta$). This assumption ensures that entrepreneurs borrow from households. Similar to households, entrepreneurs' aggregate consumption index is the following nest of goods 1 and 2

$$c_t^{Ej} = \left[(c_{1t}^{Ej})^{\frac{\eta-1}{\eta}} + (c_{2t}^{Ej})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$$

where c_{1t}^{Ej} is consumption of good 1 and c_{2t}^{Ej} is consumption of good 2. The flow budget constraint is

$$c_t^{Ej} + w_t l_t^{Ej} + R_{t-1} b_{t-1}^{Ej} = b_t^{Ej} + p_{jt} y_{jt} \tag{4.6}$$

where l_{jt}^{Ej} is the hours of work they employ, b_{jt}^{Ej} is borrowing from households, and y_{jt} is good j produced by type j entrepreneurs. Entrepreneurs face the following borrowing constraint

$$b_t^{Ej} \leq \bar{b}_t^{Ej} \tag{4.7}$$

where $\bar{b}_t^{Ej}$ follows an exogenous AR(1) process for the type 1 entrepreneur but remains constant for the type 2 entrepreneur. Note that equation (4.7) binds at the steady state because entrepreneurs' discount factor is smaller than that of households. I further assume that shocks are small enough that this equation always binds.

Type j entrepreneurs produce good j using the following process. All intermediate goods and final goods are produced by entrepreneurs internally. First, they produce a continuum of intermediate goods with the entrepreneur-level Cobb-Douglas technology.

$$\int_0^1 x_{jt}(i)di \leq (l_t^{Ej})^{1-\alpha} \tag{4.8}$$

where $\alpha \in [0,1]$ governs the efficiency of labor in producing output. $x_{jt}(i)$ is the intermediate good i produced by entrepreneur j at time t. Each intermediate good can be stored in inventory before being used to produce a final good

$$\begin{aligned} y_{jt}(i) + \text{inven}_{jt}(i) &\leq \text{inven}_{j,t-1}(i) + x_{j,t}(i) \\ \text{inven}_{jt}(i) &\geq 0 \end{aligned} \tag{4.9}$$

where $\text{inven}_{jt}(i)$ is type j entrepreneurs' inventory for each product i and $y_{jt}(i)$ is the sum of the last period's inventory ($\text{inven}_{j,t-1}(i)$) and what is left after producers store their intermediate goods ($x_{jt}(i)$) in inventory ($\text{inven}_{jt}(i)$) during this period. Then, they produce the type j final good by combining multiple intermediate goods with a CES technology:

$$y_{jt} \equiv \Big[\int_0^1 \theta(i)(y_{jt}(i))^{\rho} di\Big]^{\frac{1}{\rho}} \tag{4.10}$$

where $\theta(i)$ is product-level idiosyncratic shock to an intermediate good ($y_{jt}(i)$). I assume that there is an information lag, that is, $\theta(i)$ is realized after entrepreneurs produce the intermediate good $x_{jt}(i)$. In this way, entrepreneurs in this model have an incentive to store goods in inventory to prevent product stock-out. For analytical tractability, I further assume that $\theta(i)$ is drawn from the Pareto distribution.

Note that entrepreneurs hold inventory to avoid product stock-out, not to hedge against a decrease in their borrowing capability. This formulation is consistent with the micro level empirical evidence, because companies do not seem to hold inventory before the Lehman failure to hedge against the credit supply shock, as shown in Table 2. However, the effect on output price is likely to be larger if entrepreneurs hold inventory to hedge against the credit supply shock as they are more likely to liquidate inventory due to the shock.

Entrepreneur-Level Optimality Conditions

The first-order conditions with entrepreneur-level variables are as follows. Detailed derivations of the first order conditions are presented in Appendix A, and since entrepreneurs have identical first-order conditions, I suppress the notation of the entrepreneur, Ej.

The Euler equation for the entrepreneur is

$$\frac{1}{c_t^{\sigma_c}} = E_t \frac{\gamma R_t}{c_{t+1}^{\sigma_c}} + \eta_t \tag{4.11}$$

where η_t is the Lagrange multiplier associated with the borrowing constraint (equation 4.7). A decrease in borrowing capability leads to an increase in η_t and in the marginal utility of consumption.

The labor demand equation for the entrepreneur j is

$$w_t = (1-\alpha)\frac{x_{jt}R^I(\theta^*_{jt})G(\theta^*_{jt})^{\frac{1-\rho}{\rho}}}{l_t}\Big\{\frac{\eta-1}{\eta}p_{jt}\Big\} \tag{4.12}$$

where θ^*_{jt} is an optimal cutoff value of the idiosyncratic shock, $R^I(\theta^*_{jt})$ measures the rate of return to inventory investment, and $G(\theta^*_{jt})$ is the function of θ^*_{jt}. Entrepreneurs face a product stockout if the idiosyncratic shock, $\theta(i)$, is larger than θ^*_{jt}, but they have an excess supply if $\theta(i)$ is smaller than θ^*_{jt}. The optimal cutoff value θ^*_{jt} is time-varying and determined at the point at which the marginal cost of production equals the expected marginal benefit. The mathematical expression of each term is in Appendix A.

Note that without the terms related to the optimal cutoff θ^*_{jt} $\left(R^I(\theta^*_{jt})G(\theta^*_{jt})^{\frac{1-\rho}{\rho}}\right)$, the equation collapses to the standard labor demand equation with monopolistic competition. Then, the borrowing shock does not change the labor demand in this simple model. Allowing inventory in the model generates a variable markup between the marginal product of labor and real wages and creates an important change in the labor demand. Given that entrepreneurs liquidate inventory, inefficiency increases as a result of more products being on stock-out, which leads entrepreneurs to lay off workers.

The inventory demand equation is

$$\frac{R^I(\theta^*_{jt})G(\theta^*_{jt})^{\frac{1-\rho}{\rho}}p_{jt}}{c_t^{\sigma_c}} = \gamma R^I(\theta^*_{jt})E_t\left\{\frac{R^I(\theta^*_{j,t+1})G(\theta^*_{j,t+1})^{\frac{1-\rho}{\rho}}p_{j,t+1}}{c_{t+1}^{\sigma_c}}\right\} \tag{4.13}$$

The consumption-smoothing motive generates a change in optimal cutoff θ^*_{jt}, compelling entrepreneurs to liquidate inventory. The good 1 demand and good 2 demand are the same as in the household optimality conditions.

4.1.3 Calibration and Results

Calibration of parameters is standard, as in Table 13. I assume $\theta(i)$ is drawn from the Pareto distribution: $F(\theta) = 1 - \left(\frac{1}{\theta}\right)^{\xi}$. $\bar{b}_t$ follows an exogenous AR(1) process $\ln(\bar{b}_t) = \rho^{\bar{b}}\ln(\bar{b}_{t-1}) + \epsilon^{\bar{b}}_t$, where $\sigma_{\bar{b}}$ is the standard error of the $\epsilon^{\bar{b}}_t$. Calibration of inventory parameters (ξ and η) follows Wen (2011) and matches the inventory-investment-to-GDP ratio of 0.01 and the inventory-to-sales ratio of 1. Demand elasticity of substitution is calibrated based on the median value of the estimated elasticity used in section 3.3.

The simple model is designed to capture the micro-level empirical evidence and formalize the fire sale of inventory hypothesis. A thought experiment here is an exogenous decrease in type 1 entrepreneur's borrowing capability. This decrease reflects the differential change in producers' credit supply condition analyzed with the micro-level data. When the shock is realized, there is a large increase in the marginal utility of entrepreneur 1 because he or she wants to *smooth* the consumption. This consumption-smoothing motive enables entrepreneur 1 to aggressively liquidate the inventory and sell it at a low price in the product market to generate extra revenue. However, because entrepreneur 1 initially holds inventory to avoid the stock-out of products—not to hedge against the credit supply shock—this fire sale leads to a greater stock-out of products and corresponding larger inefficiency. This inefficiency, in turn, makes entrepreneur 1 lay off workers.

Figure 5 shows the impulse response function of relative output price, inventory, market share, and employment. Note that the model generates a temporary decrease in the relative

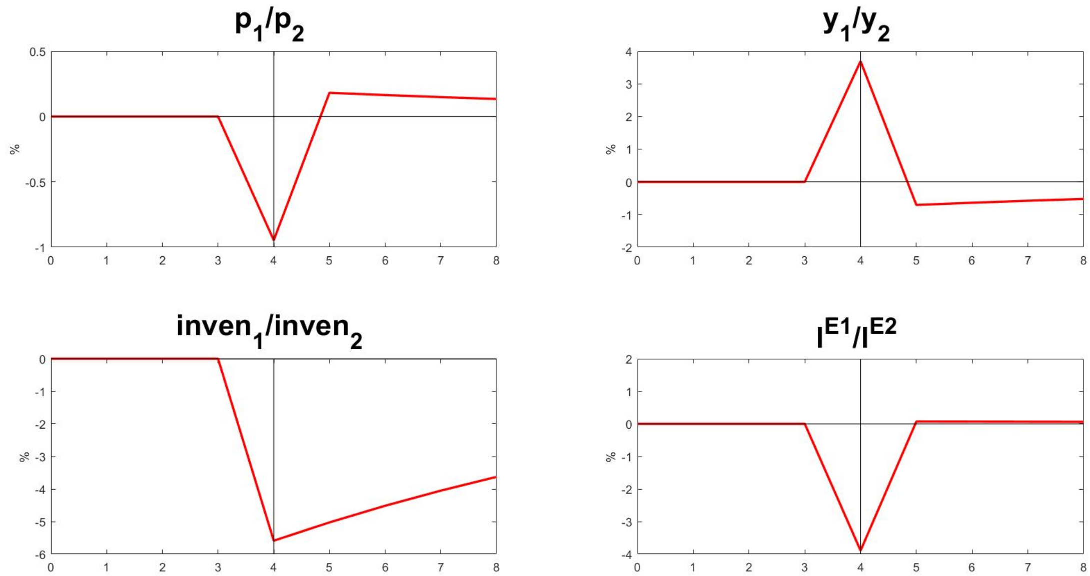
Table 13: Calibration

Simple model		
Parameter	Meaning/governing	Value
α	Labor share	0.33
β	HH discount factor	0.99
γ	E1 and E2 discount factor	0.98
σ_c	Intertemporal elasticity	2
σ_l	Frisch elasticity	1
ρ	Production elasticity of substitution	0.1
ξ	Product-level shock distribution parameter	3
η	Demand elasticity of substitution (producer)	3.9
$\rho^{\bar{b}}$	Borrowing shock parameter	0.95
$\sigma_{\bar{b}}$	Borrowing shock parameter	1

Extended model		
Parameter	Meaning/governing	Value
ψ_k	Capital adjustment cost	15 or 0
ϕ	Price rigidity	0.75
ϵ	Demand elasticity of substitution (product)	6.9
δ	Capital depreciation	0.03
r_R	Persistence parameter in the Taylor rule	0.73
r_π	Inflation parameter in the Taylor rule	0.27
r_Y	Output parameter in the Taylor rule	0.13
$\sigma_{\bar{b}}$	Borrowing shock parameter	10

Figure 5: Differential Response of Price, Output, Inventory, and Employment

with respect to the Negative Credit Supply Shock



Note. The top-left panel shows the dynamics of relative price, the top-right panel shows the dynamics of relative market share, the bottom-left panel shows the dynamics of relative inventory, and the bottom-right panel shows the dynamics of relative labor due to the negative credit supply shock to type 1 entrepreneurs.

output price, as shown in Table 4 and Figure 3. This relative price dynamics occurs because entrepreneur 1 decreases employment and production, but increases sales as he or she draws down inventory, consistent with Table 6.

4.2 Extended Model

I extend the simple model by adding money, price rigidity, a central bank, and capital investment. The simple model presented in section 4.1 is a purely real model and cannot speak to inflation dynamics. To examine the aggregate inflation dynamics, I introduce money into the household utility, retailers with Calvo-Yun price rigidity, and the central bank that follows the Taylor rule. I assume that real money balance is additively separable from consumption and labor in the household utility function so that the quantity of money has no implications for the rest of the model. This extension is a parsimonious way to convert a real model to a nominal model. Additionally, I introduce capital investment with a quadratic adjustment cost in addition to inventory. Capital is another form of saving and can be used to smooth the consumption, similar to inventory. When there is an exogenous decrease in borrowing capability, entrepreneurs can either liquidate inventory or disinvest in capital to increase their current consumption. This substitution is governed by the capital adjustment cost. If the capital adjustment cost is high, entrepreneurs sell inventory and lower their output prices, but with a low capital adjustment cost, entrepreneurs instead disinvest in capital to smooth consumption.

In the extended model, retailers, not households, purchase products from entrepreneurs. Two identical types of retailers correspond to the two identical types of entrepreneurs, and each type produces differentiated products that face CES demand. Retailers use what they purchase from entrepreneurs, differentiate the products, and sell to consumers. In this process, they face Calvo-Yun price rigidity in changing their output prices.[31] Type j retailers' optimal condition can be characterized by the following equation:

$$E_t \sum_{s=0}^{\infty} (\beta\phi)^s \frac{u'(c_{t+s})}{u'(c_t)} \left(\frac{p_{jt}(z)}{p_{t+s}} - \frac{\epsilon - 1}{\epsilon} \frac{p^w_{j,t+s}}{p_{t+s}} \right) y_{j,t+s}(z) = 0 \tag{4.14}$$

where $p_{jt}(z)$ is the "reset" price, $y_{j,t+s}(z)$ is the corresponding demand, ϕ is the share of firms that can change the price, and ϵ is the elasticity of substitution across retailers within each type. This condition states that the discounted expected value of marginal revenue is equal to the discounted expected marginal cost.

The central bank follows the Taylor rule:

$$R_t = (R_{t-1})^{r_R} (\pi_{t-1}^{1+r_\pi} (y_{t-1}^{\text{GDP}} / y^{\text{GDP}})^{r_Y} \bar{rr})^{1-r_R} e_{R,t} \tag{4.15}$$

where R_t is the interest rate at time t and y_t^{GDP} is total production in the economy at time t. I allow for persistence in the interest rate R_t and calibrate the parameters following Iacoviello (2005). Allowing other realistic parameters does not make a qualitative difference in the results.

Finally, I introduce capital investment in the entrepreneurs' flow budget constraint (4.6).

$$I_{jt} = k_{jt} - (1 - \delta) k_{j,t-1} + \xi(k_{jt}, k_{j,t-1})$$

where I_{jt} is capital investment of entrepreneur j at time t, k_{jt} is the capital used by entrepreneur j at time t, δ is the capital depreciation, and $\xi(k_{jt}, k_{j,t-1})$ is a quadratic adjustment cost and equals $\frac{\psi_k}{2}\left(\frac{k_t}{k_{t-1}} - 1\right)^2 k_{t-1}$. Unlike inventory, capital investment is a perfect substitute for consumption and can be used to smooth the consumption without changing the output price. This capital is used in production and the production function (4.8) is replaced by the following equation

$$\int_0^1 x_{jt}(i) di = k_{jt}^{\alpha} l_{jt}^{1-\alpha} \tag{4.16}$$

The key parameter in this setup is the capital adjustment cost. In the benchmark case,

[31] With the log-linearization, this extension is the same as introducing Rotemberg price adjustment cost at the entrepreneur level.

I assume that the capital adjustment cost parameter, ψ_k, equals 15. This parameter is large enough such that entrepreneurs cannot disinvest enough capital to smooth their consumption when borrowing capability decreases. Borrowing-constrained entrepreneurs instead liquidate inventory and lower their prices to generate extra sales from the product market to smooth consumption. The counterfactual scenario is when there is no capital adjustment cost, $\psi_k = 0$. In this case, rather than liquidating their inventory, entrepreneurs disinvest in capital to smooth consumption. The magnitude of the borrowing shock, $\sigma_{\bar{b}}$, is calibrated to be 10 to match the relative decrease in the output price of 15% due to the negative borrowing shock to entrepreneur 1. This 15% decrease is observed in the micro-level data when I regress the change in the log of output price on the dummy variable, which equals 1 if the credit supply shock measure is smaller than its median value, and 0 otherwise. This result is reported in Appendix E. Calibration of other parameters in the extended model is standard, as in Table 13. Parameters in the Taylor rule follow Iacoviello (2005)[32], and the demand elasticity across products follow the median value used in section 3.3. I assume that the shock is persistent given that the bank shock is likely to affect firms persistently. Using a temporary shock, in fact, magnifies the increase in the medium-run inflation. The entrepreneur facing a temporary shock accumulates inventory immediately in the next period, whereas an entrepreneur facing a persistent shock slowly stocks inventory and raises the price.

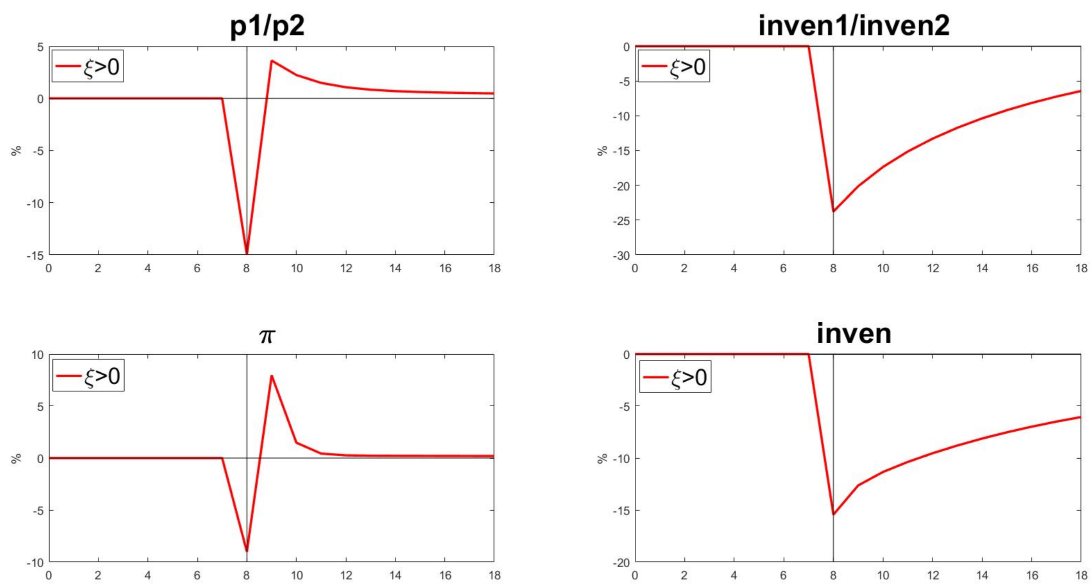
Based on the benchmark calibration, I find that a drop in entrepreneur 1's borrowing capability leads to a decrease in relative price and inventory and a drop in *aggregate* inflation and inventory. The results are reported in Figure 6. A decrease in relative variables in this model is consistent with the micro-level empirical analysis, the same as the simple model presented in section 4.1. At the same time, this model generates a large decrease in aggregate inflation and inventory dynamics. Both aggregate and relative dynamics are driven by the fire sale of inventory mechanism. Entrepreneur 1—who faces a negative credit supply shock—aggressively liquidates inventory and lowers the price to generate extra sales to smooth consumption. In the next period, entrepreneur 1 starts to accumulate inventory and raise the price, leading both the relative price and aggregate inflation to increase.

I compare the impulse response generated from the model with the U.S. producer price index and inventory data, as shown in Figure 7. The magnitude of the shock, which is calibrated to match the change in the relative price observed in the micro-level data, explains the approximately 10% drop in the output price. This drop in inflation explains almost all of the drop in the producer price index during the financial panic of 2008 under the standard parameter calibration. Then, inflation overshoots in the next period because entrepreneur 1 raises the price back to the original level. This increase is consistent with the "missing disinflation puzzle", which discusses that inflation did not fall during the 2007-09 recession despite high unemployment and low

[32] Allowing other parameters does not change the qualitative results. To motivate a zero lower bound, I also fix the interest rate for four quarters and then allow it to follow the Taylor rule. This analysis makes the results even stronger since the central bank cannot use monetary policy to stabilize inflation.

Figure 6: Aggregate and Differential Response of Price and Inventory

with respect to the Negative Credit Supply Shock



Note. The top-left panel shows the dynamics of relative output price, the top-right panel shows the dynamics of relative inventory, the bottom-left panel shows the dynamics of aggregate inflation, and the bottom-right panel shows the dynamics of average inventory due to the negative credit supply shock to type 1 entrepreneurs.

demand. The credit supply shock counteracts the usual deflationary force and explains this puzzle in my model, consistent with the previous literature. In explaining the stable medium-run inflation dynamics, however, I propose a new mechanism based on the micro-level empirical analysis that explains not only the "missing disinflation puzzle" but also the short-run drop in the inflation. The model also generates a large decrease in inventory, consistent with the data.

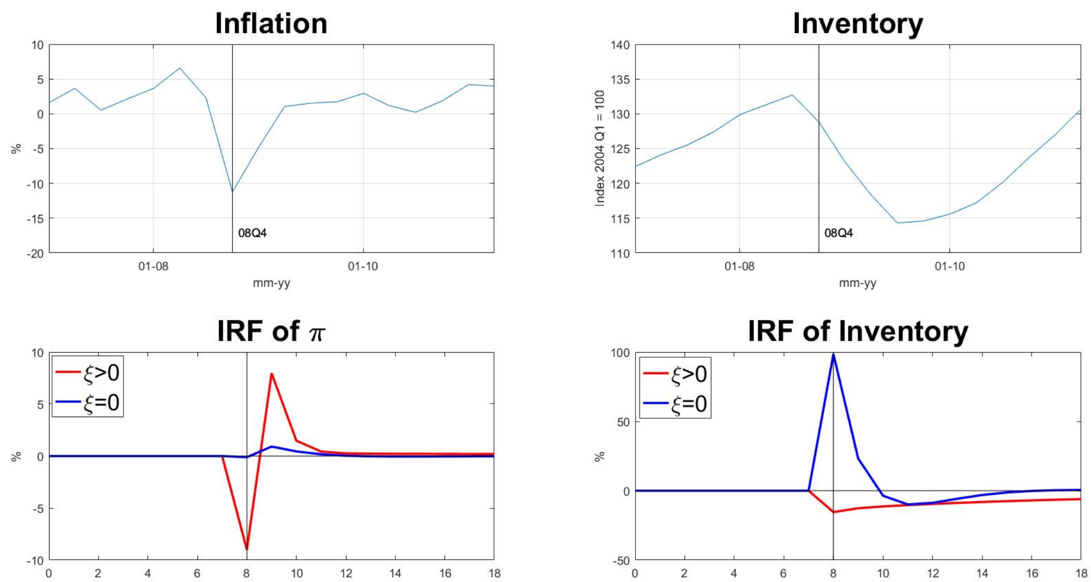
Finally, I set the capital adjustment cost to be 0 to compare it with the case when the entrepreneur does not liquidate inventory but instead disinvests capital. As shown in Figure 6, aggregate inflation does not change much in this case, because the entrepreneur can smooth the consumption by disinvesting capital and use this resource to consume directly, rather than liquidating inventory and decreasing the price. Additionally, in this case, there is a large increase in inventory at the time of the shock. If the entrepreneur raises consumption by lowering the capital investment, production in the next period falls despite a moderately large demand, giving an incentive to hoard inventory at the time of the shock in order to meet the demand in the next period. Note that the entrepreneur chooses to disinvest capital instead of liquidating inventory when the capital adjustment cost is 0. This behavior is due primarily to increased product stock-out as a result of liquidating inventory. When the inventory is liquidated, there is a greater stock-out for producers because of idiosyncratic shock, leading to larger inefficiency for the entrepreneur. Overall, this comparison shows that without the fire sale of inventory, there is no dramatic change in inflation dynamics in the model, which is inconsistent with the data.

5 Conclusion

In this paper, 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 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 first showing that in the data, both aggregate inflation and inventory fall but corporate cash holdings rise. I further show that firms that face a negative credit supply shock reduce their inventories and increase their market share and cash holdings, supporting the hypothesis. I then build a simple dynamic general equilibrium model to formalize this mechanism explicitly and to discuss aggregate inflation dynamics. The model features two competing mechanisms: the fire sale of inventory channel emphasized in this paper and the conventional production effect of credit supply shock discussed in previous studies. As a result of the adverse credit supply shock for a group of producers, the model predicts a drop in the relative price by firms that face a negative credit supply shock, consistent with the micro-level empirical evidence. At the same time, the model features aggregate inflation dynamics consistent with observations for the middle of the financial panic, which cannot be

Figure 7: Aggregate Response of Price and Inventory

Compared with the Data



Note. The top-left panel shows the U.S. inflation dynamics observed in the data during the financial panic, and the top-right panel shows the U.S. inventory dynamics observed in the data during the same period. The bottom-left panel shows the dynamics of aggregate inflation due to the negative credit supply shock to type 1 entrepreneurs, and the bottom-right panel shows the dynamics of average inventory due to the same shock.

predicted without incorporating the "fire sale" of inventory mechanism in the model.

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

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A Derivation of Entrepreneur-Level Optimality Conditions

Denote $x_{jt} \equiv \int_0^1 x_{jt}(i)di$, $s_t \equiv \text{inven}_t$ and $\{\eta_t, \lambda_{3,t}, \lambda_{2,t}(i), \xi_t(i), \lambda_{1,t}\}$ as the non-negative Lagrangian multipliers for the constraints (4.7)-(4.10), respectively. For simplicity, suppress notation for entrepreneurs Ej since the solution is identical. First-order conditions for $\{c_t, b_t, l_t, y_{jt}(i), x_{jt}(i), s_{jt}(i), c_{1t}, c_{2t}\}$ are:

$$\frac{1}{c_t^{\sigma_c}} = \lambda_{1,t} \tag{A.1}$$

$$\lambda_{1,t} - \eta_t - \gamma E_t \lambda_{1,t+1} R_t = 0 \tag{A.2}$$

$$\lambda_{1,t} w_t = \lambda_{3,t}(1-\alpha)\frac{x_t}{l_t} \tag{A.3}$$

$$\lambda_{1,t}\frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}} \theta_t(i) y_t(i)^{\rho-1} = \lambda_{2,t}(i) \tag{A.4}$$

$$\lambda_{3,t} = E_t^i \lambda_{2,t}(i) = \int \lambda_{2,t}(i) dF(\theta_t) \tag{A.5}$$

$$\lambda_{2,t}(i) = \gamma E_t \lambda_{2,t+1}(i) + \xi_t(i) \tag{A.6}$$

plus relevant transversality conditions and the complementarity slackness condition, $s_t(i)\xi_t(i) = 0$, for all $i \in [0,1]$. Notice that equation (A.5) shows the timing lag with E^i.

Decision Rules for Inventories

The key to solving the decision rules in the intermediate goods sector is to determine the optimal stock, $x_{jt}(i) + s_{jt}(i)$, based on the distribution of θ. Using the iterated expectation,

$$\lambda_{2,t}(i) = \gamma E_t \lambda_{3,t+1} + \xi_t(i) \tag{A.7}$$

There are two possible cases to consider:

- CASE A: Suppose $\theta(i) \le \theta^*$. We then have $\xi(i) = 0, s(i) \ge 0$, and $\lambda_{2,t}(i) = \gamma E_t \lambda_{3,t+1}$. The budget constraint (4.9) implies that $y_{jt}(i) \le x_{jt}(i) + s_{j,t-1}(i)$. Because equation (A.4) implies $y_{jt}(i) = \left[\frac{\lambda_{1,t}\frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}} \theta_t(i)}{\gamma E_t \lambda_{3,t+1}}\right]^{\frac{1}{1-\rho}}$, we have $\theta(i) \le \left[x_{jt}(i) + s_{j,t-1}(i)\right]^{1-\rho}\left[\frac{\gamma E_t \lambda_{3,t+1}}{\lambda_{1,t}\frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}}}\right] \equiv \theta^*$, which defines the optimal cutoff value θ^* and the optimal stock as $x_{jt}(i) + s_{j,t-1}(i) \equiv \left[\frac{\lambda_{1,t}\frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}} \theta^*}{\gamma E_t \lambda_{3,t+1}}\right]^{\frac{1}{1-\rho}}$.
- CASE B: In the case where $\theta(i) > \theta^*$, we have $\xi_t(i) > 0$, $s(i) = 0$, and $y_{jt}(i) = x_{jt}(i) + s_{j,t-1}(i) \equiv \left[\frac{\lambda_{1,t}\frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}} \theta^*}{\gamma E_t \lambda_{3,t+1}}\right]^{\frac{1}{1-\rho}}$. Equation (A.4) then implies $\lambda_{2,t}(i) = \gamma E_t \lambda_{3,t+1}\frac{\theta_t(i)}{\theta^*} > \gamma E_t \lambda_{3,t+1}$.

Given these two possibilities, equation (A.7) can be written as

$$\lambda_{3,t} = \int_{\theta(i)\leq\theta^*} (\gamma E_t \lambda_{3,t+1}) dF(\theta) + \int_{\theta(i)>\theta^*} (\gamma E_t \lambda_{3,t+1}) \frac{\theta_t(i)}{\theta^*} dF(\theta) \tag{A.8}$$

where the left-hand side is the marginal cost of inventory, the first term on the right-hand side is the shadow value of inventory when there is excess supply, and the second term is the shadow value of inventory when there is a stock-out. Thus, the optimal cutoff value is determined at the point where the marginal cost equals the expected marginal benefit. Because aggregate variables are independent of idiosyncratic shocks, equation (A.8) can be written as

$$\lambda_{3,t} = \gamma E_t \lambda_{3,t+1} R^I(\theta_t^*) \tag{A.9}$$

where $R^I(\theta^*) \equiv F(\theta^*) + \int_{\theta(i)>\theta^*} \frac{\theta(i)}{\theta^*} dF(\theta) > 1$ measures the rate of returns to liquidity or inventory investment. Notice that the optimal cutoff value θ_t^* is time-varying and that $\frac{dR^I(\theta^*)}{d\theta^*} < 0$.

Given the aggregate economic condition, equation (A.9) solves the optimal cutoff value as $\theta_t^* = (R^I)^{-1}(\lambda_{3,t}/\beta E \lambda_{3,t+1})$. The decision rules for $x_{jt}(i)$ are given by

$$x_{jt}(i) + s_{j,t-1}(i) = \left[\frac{\lambda_{1,t} \frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}} \theta^*}{\gamma E_t \lambda_{3,t+1}} \right]^{\frac{1}{1-\rho}} \tag{A.10}$$

$$y_{jt}(i) = \left[\frac{\lambda_{1,t} \frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}}}{\gamma E_t \lambda_{3,t+1}} \right]^{\frac{1}{1-\rho}} \times \min \left\{ \theta_t(i)^{\frac{1}{1-\rho}}, \theta_t^{*\frac{1}{1-\rho}} \right\} \tag{A.11}$$

$$s_t(i) = \left[\frac{\lambda_{1,t} \frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}}}{\gamma E_t \lambda_{3,t+1}} \right]^{\frac{1}{1-\rho}} \times \max \left\{ \theta_t^{*\frac{1}{1-\rho}} - \theta_t(i)^{\frac{1}{1-\rho}}, 0 \right\} \tag{A.12}$$

The shadow price of inventory i is determined by

$$\lambda_{2,t}(i) = \gamma E_t \lambda_{3,t+1} \times \max \left\{ 1, \frac{\theta(i)}{\theta^*} \right\} \tag{A.13}$$

Inventory: Aggregate Dynamics

Defining the aggregate variables, $Y_{jt} \equiv \int y_{jt}(i)di$, $s_{jt} \equiv \int s_{jt}(i)di$, and aggregating the decision rules (A.10)-(A.12) under the law of large numbers gives

$$Y_{jt} = \left[\frac{\lambda_{1,t} \frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}}}{\gamma E_t \lambda_{3,t+1}} \right]^{\frac{1}{1-\rho}} D(\theta_t^*) \tag{A.14}$$

$$x_{jt} + s_{j,t-1} = Y_{jt} \frac{D(\theta_t^*) + H(\theta_t^*)}{D(\theta_t^*)} \tag{A.15}$$

$$s_{jt} = Y_{jt} \frac{H(\theta_t^*)}{D(\theta_t^*)} \tag{A.16}$$

and combining and aggregating the first-order conditions (A.13) and (A.4) lead to

$$\lambda_{3,t} = \lambda_{1,t} R^I(\theta_t^*) G(\theta^*)^{\frac{1-\rho}{\rho}} \Big\{ \frac{\eta - 1}{\eta} \Big(\frac{y_t}{y_{jt}} \Big)^{\frac{1}{\eta}} \Big\} \tag{A.17}$$

where

$$\begin{aligned}
D(\theta^*) &\equiv \int_{\theta(i) \leq \theta^*} \theta(i)^{\frac{1}{1-\rho}} dF(\theta) + \int_{\theta(i) > \theta^*} \theta^{*\frac{1}{1-\rho}} dF(\theta) > 0 \\
H(\theta^*) &\equiv \int_{\theta(i) \leq \theta^*} \Big[\theta^{*\frac{1}{1-\rho}} - \theta(i)^{\frac{1}{1-\rho}} \Big] dF(\theta) > 0 \\
\theta^{*\frac{1}{1-\rho}} &= D(\theta^*) + H(\theta^*) \\
G(\theta^*) &\equiv \int_{\theta(i) \leq \theta^*} \theta(i)^{\frac{1}{1-\rho}} dF(\theta) + \int_{\theta(i) > \theta^*} \theta(i) \theta^{*\frac{\rho}{1-\rho}} dF(\theta) > D(\theta^*)
\end{aligned}$$

The entrepreneur-level budget constraint (4.6) can be written as

$$c_t + w_t l_t + R_{t-1} b_{t-1} - b_t = p_{jt} \frac{y_{jt}}{Y_{jt}} \Big[l_t^{1-\alpha} + s_{j,t-1} - s_{jt} \Big]$$

where $\frac{y_{jt}}{Y_{jt}} = G(\theta^*)^{\frac{1}{\rho}} D(\theta^*)^{-1}$ measures the hypothetical relative price of intermediate goods with respect to the final good.

The first order conditions with entrepreneur-level variables are as follows:

$$w_t = (1-\alpha) \frac{x_{jt} R^I(\theta_{jt}^*) G(\theta_{jt}^*)^{\frac{1-\rho}{\rho}}}{l_t} \Big\{ \frac{\eta - 1}{\eta} p_{jt} \Big\} \tag{A.18}$$

$$\frac{R^I(\theta_{jt}^*) G(\theta_{jt}^*)^{\frac{1-\rho}{\rho}} p_{jt}}{c_t^{\sigma_c}} = \gamma R^I(\theta_{jt}^*) E_t \Big\{ \frac{R^I(\theta_{j,t+1}^*) G(\theta_{j,t+1}^*)^{\frac{1-\rho}{\rho}} p_{j,t+1}}{c_{t+1}^{\sigma_c}} \Big\} \tag{A.19}$$

$$c_{1t} = \left(\frac{p_{1t}}{p_t} \right)^{-\eta} c_t, j = 1, 2 \tag{A.20}$$

$$c_{2t} = \left(\frac{p_{2t}}{p_t} \right)^{-\eta} c_t, j = 1, 2 \tag{A.21}$$

where

The equations correspond to the Euler equation (4.11), labor demand (A.18), inventory demand (A.19), good 1 demand (A.20), and good 2 demand (A.21)

The aggregate budget constraints are:

$$c_t + w_t l_t + R_{t-1} b_{t-1} - b_t = p_{jt} \frac{y_{jt}}{Y_{jt}} \Big[a_t (l_t)^{1-\alpha} + s_{j,t-1} - s_{jt} \Big] \tag{A.22}$$

$$s_{jt} = Y_{jt} \frac{H(\theta_{jt}^*)}{D(\theta_{jt}^*)} \tag{A.23}$$

$$x_{jt} + s_{j,t-1} = Y_{jt} \frac{D(\theta^*_{jt}) + H(\theta^*_{jt})}{D(\theta^*_{jt})} \tag{A.24}$$

$$b_t = \bar{b}_t \tag{A.25}$$

where $\frac{y_{jt}}{Y_{jt}} \equiv G(\theta^*)^{\frac{1}{\rho}} D(\theta^*)^{-1}$ measures the relative price of intermediate goods with respect to the final good.

B Measurement of Variables in Figure 1

The consumer price index in Figure 1 (a), producer price indexes in Figure 1 (b), and aggregate inventory in Figure 1 (d) were downloaded from the FRED Economic Data.[33]. The aggregate corporate cash holding is measured using the quarterly Compustat database, which was downloaded from the WRDS. The Compustat database is a listed firm-level database compiled by Standard and Poor's and includes detailed firm-level information including corporate cash holdings. Following Bates et al. (2009), I exclude financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999).[34] I require firms to have a non-negative and non-missing measure of cash holdings. In constructing aggregate corporate cash holdings, I sum up corporate cash holdings across firms within each quarter. I adjust for the seasonality in cash holdings by using the X-13ARIMA-SEATS Seasonal Adjustment Program from the Census to obtain the aggregate series plotted in Figure 1 (d).[35]

The scanner price index in Figure 1 (c) is measured using the ACNielsen Homescan Panel database discussed in Section 2. I first divide my sample into two groups based on the measure of the credit supply shock (ΔL_f) constructed in Section 3.1. If a firm's credit supply shock measure is larger than the 80th percentile of the credit supply shock measure, I assume that firm faces a large negative credit supply shock. On the other hand, if a firm's credit supply shock measure is smaller than the 20th percentile of the credit supply shock measure, I assume that firm faces a small negative credit supply shock. Using another threshold, such as the 75th percentile and 25th percentile, shows similar results.

For each group of firms, I construct the price index in the following way. I take a geometric average of price across UPC within firm-group-time, and then take a geometric average of price across firm within group-time:

$$P_{fgt} = \left(\prod_{u \in \Omega_{fgt}} P_{ut} \right)^{1/N_{fgt}}, \quad P_{gt} = \left(\prod_{f \in \Omega_{gt}} P_{fgt} \right)^{1/N_{gt}}$$

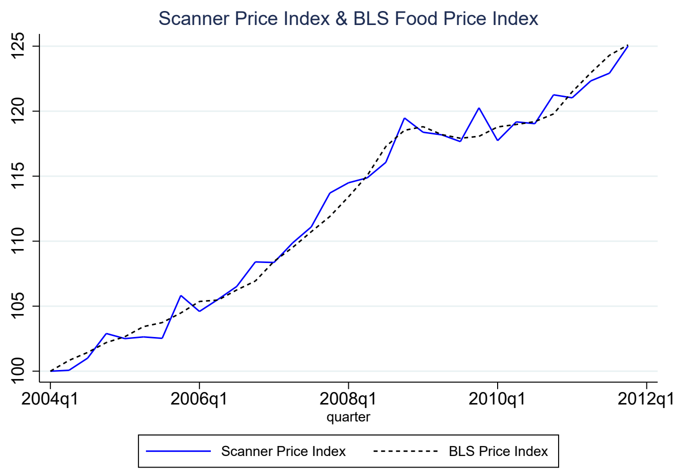
These indexes correspond to the price index at the firm-group-level and group-level based

[33]Visit https://fred.stlouisfed.org/ to download the relevant variables

[34]financial firms might increase cash holdings to meet the capital requirement, rather than liquidating inventory or other economic reasons. The cash holdings of firms in the utilities can be subject to regulatory supervision.

[35]See https://www.census.gov/srd/www/x13as/ for more information.

Figure 8: Comparison with the Official Price Index



The scanner price index is measured based on price and quantity data available in the ACNielsen Homescan Panel database. The BLS food price index is the official price index downloaded from FRED.

on the nested-CES demand system that does not incorporate the variety-quality correction as discussed in Section 3.2. I then use the following Tornqvist price index to construct aggregate price index:

$$\frac{P_t}{P_{t_0}} = \prod_{g \in \Omega} \left(\frac{P_{gt}}{P_{gt_0}} \right)^{(\varphi_{gt} + \varphi_{gt_0})/2}$$

where t_0 is the base time (2004:Q1), and φ_{gt} is a market share weight for group g at time t.

I checked to see how well this index follows the official price index for the United States. I construct aggregate scanner price index by using all price and quantity available in the ACNielsen Homescan Panel database. I plot this index along with the BLS food price index downloaded from FRED to check the validity of index I constructed. As shown in Figure 8, the scanner price index closely follows the official price index.

C Robustness Checks

C.1 Different Timing of the Credit Supply Shock

A potential concern related to the definition of the pre- and post-treatment periods is that the period between 2007:Q3 and 2008:Q2 is not used in the main regression analysis. I did not use this period because it is unlikely to be suitable either for the pretreatment period because of the moderate degree of credit market stress at this time or for the post-treatment period because I cannot exploit the surprising nature of the Lehman bankruptcy. Excluding this period, however, raises questions about what occurred to firms that faced a negative credit supply shock during this time. For example, firms might increase their output prices in response to the modest degree of credit market stress between the pre- and post-Lehman periods but then drop their output prices when they face an extreme degree of negative credit supply shock, such as the Lehman bankruptcy. In addition, although the negative relationship between the price and quantity of loans after the Lehman failure in Figure 2 ensures that this period is characterized by a shift in credit supply, Duchin et al. (2010) indicate that demand-side factors became more important during this period.[36] They suggest the period before the Lehman failure is more appropriate for studying the effect of a credit supply shock, at least for corporate investment.

I utilize three other definitions of pre- and post-treatment periods that incorporate 2007:Q4 to 2008:Q2 in order to corroborate the empirical findings, as shown in Table 14. The first two columns report the results by defining 2007:Q4 to 2008:Q2 as a post-treatment period. Using the main credit supply shock variable, I still find that the negative credit supply shock leads firms to decrease their output prices. These results not only ease concerns related to the demand-side effects that might be stronger after the Lehman failure but also suggest that the effect is robust to the moderate degree of credit market stress, consistent with the external validity check in section 3.6.3. In addition, given the somewhat large degree of credit market stress in this period, this timing provides a useful placebo test for the measure of the Lehman failure. I find that the Lehman failure does not lead firms to change their output prices in this period, additionally validating the measure of the Lehman failure. In addition, I define 2007:Q4 to 2008:Q2 as a pre-Lehman period and find that the effect of credit supply shock on price is even stronger than it is in the main regression analysis.

C.2 Retailer Behavior

In this section, I address concerns related to retailer behavior and conduct three additional empirical analyses to show that the qualitative results in this article are robust to retail-level decisions. A potential concern regarding the regression analysis is that I observe the prices of products that households purchase, not the prices that firms set. Using these prices would not be a problem for retailers in my sample but would generate some discrepancy for manufacturers because they need to sell their products to retailers to reach their final consumers. For this subsample, if retailers do not completely pass through manufacturers' output prices, the estimated coefficient could be biased. While complete pass-through is assumed in many macroeconomic and international trade models with the CES demand system and monopolistic competition, in reality, retailers are likely to adjust their margins as the result of a decrease in their costs.

[36] In choosing the post-treatment period, however, Duchin et al. (2010) examine the relationships between corporate investment, Tobin's Q, cash flow, and initial corporate cash holdings, not the credit market. In particular, the bank shock I use generates an entirely different variation than the initial cash holdings.

Table 14: Robustness: Different Pre- and Post-Treatment Periods

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \ln P_{fg}$ (Pre-Lehman)		$\Delta \ln P_{fg}$ (Post-Lehman)			
	ΔL_f (Pre-Lehman)		ΔL_f (Post-Lehman I)		ΔL_f (Post-Lehman II)	
	OLS	IV Lehman	OLS	IV Lehman	OLS	IV Lehman
$(-\Delta L_f)$	-3.7**	1.5	-14.4***	-16.5**	-18.5***	-16.4**
	(1.5)	(6.2)	(3.6)	(7.9)	(3.5)	(7.6)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F statistics		13.9		21.3		24.0
$E[\Delta \ln P]$	11.4	11.4	11.4	11.4	11.4	11.4
$E[\Delta \ln P{:}(-\Delta L_{p90})-(-\Delta L_{p10})]$	-8.2	3.2	-31.4	-36.1	-40.3	-35.7
Observations	1639	1639	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, 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 $\Delta \ln P_{fg}$; $\Delta \ln P_{fg}$ (Pre-Lehman): 2006:Q4-2007:Q2 to 2007:Q4-2008:Q2, $\Delta \ln P_{fg}$ (Post-Lehman): 2006:Q4-2007:Q2 to 2008:Q4-2009:Q2, ΔL_f (Pre-Lehman): 2005:Q4-2006:Q2, 2006:Q4-2007:Q2 to 2007:Q4-2008:Q2, ΔL_f (Post-Lehman I): 2006:Q4-2007:Q2 and 2007:Q4-2008:Q2 to 2008:Q4-2009:Q2, ΔL_f (Post-Lehman II): 2005:Q4-2006:Q2, 2006:Q4-2007:Q2, 2007:Q4-2008:Q2 to 2008:Q4-2009:Q2.

I argue that the estimated coefficients are at most *underestimated* because I observe only retailer-level price variation. First, studies document that retailers incompletely pass through their costs to output prices (e.g., Burstein and Gopinath 2014). If it is true that manufacturers that face a negative credit supply shock decrease their output prices, retailers that face this decrease in their costs will also decrease their output prices, but less than they decrease their cost. I rule out the case where manufacturers facing a negative credit supply shock increase their output prices, but retailers decrease their output prices due to this increase in their costs, thereby dramatically decreasing their profits. This case is very unlikely, and to the best of my knowledge, no narrative evidence or previous studies document this pattern.

To confirm that the results do not change as a result of retailers' behavior, I first allow a retail store dimension in the data and run a regression with retail store fixed effects to absorb all store-level characteristics in the sample.[37] In my main regression analysis, I use a nested CES demand system across all UPCs and firms in the data and hence abstract away from the production network effect of the retailer and manufacturer. In this way, I aggregate each product sold in different stores across retailers within manufacturers. For example, Smucker's jam is likely to be sold in different retail stores, such as CVS, Walmart, and Walgreens, and by collapsing the retailer dimension, I focus on Smucker's behavior for this particular product instead of on retailers' behavior. While this approach is a conventional way to aggregate and construct a price index and is valid when considering a large number of retailers, one might be worried that a particular type of retailer deals with a particular type of manufacturer that is more or less exposed to the credit supply shock I constructed, generating bias in the coefficient. Hence, I explicitly allow a retail store dimension in the data and remove all retail-level characteristics from the regression analysis.

Table 15 reports the results. Because I allow retail store fixed effects, credit supply shock at the retail level cannot be used. As one can see, despite the fact that I absorb retail-level variations, I still find that firms that face a negative credit supply shock decrease their output prices. Note that the estimated coefficients are approximately 3% to 5%, smaller than the estimates reported in Table 4. A plausible explanation for this finding is the incomplete pass-through. I drop all retail-level variation in the credit supply shock and use only manufacturers that must pass through retailers to sell their products to households. If there exists incomplete pass-through at the retail level, the estimated coefficients must be smaller, which is indeed what I observe.

In addition, I use only companies that are classified as retailers according to the NAICS industry code and find an even stronger result. Table 16 reports the results. Despite the smaller number of observations, based on the main measure of the credit supply shock, I still find that firms that face a negative credit supply shock decrease their output prices. The magnitude of the coefficients is larger than that reported in Table 4, again suggesting the possibility that incomplete pass-through causes the coefficient in the main analysis to be underestimated.

[37] Allowing retail-group fixed effects, which absorb all retail-group-level variation, does not alter the results.

Table 15: Robustness: Retail Store Fixed Effects

	(1)	(2)	(3)	(4)	(5)
	$\Delta\ln\tilde{P}_{\text{fgr}}$: 2006q4-2007q2 to 2008q4-2009q2				
	OLS	$(-\Delta L_f)$ instrumented using			
		Lehman	ABX	BankItem	All
$(-\Delta L_f)$	-2.9***	-5.0***	-3.9**	-3.2*	-3.9***
	(0.7)	(1.3)	(1.5)	(1.8)	(1.3)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes	Yes
Retail store FE	Yes	Yes	Yes	Yes	Yes
First-stage F statistics		25.60	16.30	24.50	13.30
J-statistics p-value					0.43
$E[\Delta\text{lnP}]$	10.2	10.2	10.2	10.2	10.2
$E[\Delta\text{lnP}:(-\Delta L_{\text{p90}})\text{-}(-\Delta L_{\text{p10}})]$	-7.2	-12.2	-9.5	-7.9	-9.6
Observations	40519	40519	40519	40519	40519

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; firm-level controls are the firm's listed status, four-digit NAICS FE, age, size indicator, 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 a lagged dependent variable; and $\Delta\ln\tilde{P}_{\text{fgr}}$ is the conventional part of the price index at the retail level that excludes the variety-quality correction.

Using bank statement items as an instrumental variable generates consistent coefficients. Using Lehman or ABX securities exposure as instruments generates larger estimates with less statistical significance, but this result is very likely due to the weak instrument for this particular subsample. As observed, the first-stage F statistics are very small. Firms in this subsample face a negative credit supply shock due to lending and the deterioration of bank balance sheets, but they are unlikely to be constrained by the Lehman exposure or ABX securities exposure.

Finally, I gather and combine manufacturer price data from the Promodata, which is also available from the Kilts Marketing Data Center to confirm the empirical findings. These data provide detailed competitive manufacturer costs and price changes for all major grocery wholesalers from major markets. The data are reported from 12 grocery wholesaler organizations that provided products to the entirety of the United States from 2006 to 2011. Despite a smaller number of observations, using these data, I still find that firms that face a negative credit supply shock decrease their output prices, as reported in Table 17. The magnitude of the coefficient is again larger than that in Table 4, suggesting that there exists incomplete pass-through. Using ABX securities as instruments generates large and statistically significant estimates, suggesting that firms that face this particular shock decrease their prices even more. Using Lehman or ABX securities exposure as instruments generates negative but statistically insignificant results likely as a result of the weak instrument problem.

Table 16: Robustness: Retailers Only

	(1)	(2)	(3)	(4)	(5)
	ΔlnP$_{\text{fg}}$: 2006q4-2007q2 to 2008q4-2009q2				
	OLS	($-\Delta L_f$) instrumented using			
		Lehman	ABX	BankItem	All
ΔL_{f}	-12.59**	-61.90	-52.09*	-13.66**	-14.87**
	(5.83)	(91.88)	(28.06)	(4.95)	(5.57)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes	Yes
First-stage F statistics		0.40	3.50	43.20	47.60
J-statistics p-value					0.20
$E[\Delta\text{lnP}]$	11.4	11.4	11.4	11.4	11.4
$E[\Delta\text{lnP}{:}\Delta L_{\text{p90}}\text{-}\Delta L_{\text{p10}}]$	-27.5	-135	-113.6	-29.8	-32.4
Observations	763	763	763	763	763

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by firm and product group; and firm-level controls are the firm's four-digit NAICS FE, bond rating, loan type, loan-year FE, multi-lead FE, and number of loans due in the post-Lehman FE

Table 17: Robustness: Manufacturer Price

	(1)	(2)	(3)	(4)	(5)
	$\Delta \ln \tilde{P}_{\text{fg}}$: 2006q4-2007q2 to 2008q4-2009q2				
	OLS	($-\Delta L_f$) instrumented using			
		Lehman	ABX	BankItem	All
($-\Delta L_f$)	-14.24**	-112.88	-37.16***	-46.77	-40.07***
	(6.47)	(267.90)	(12.64)	(38.64)	(13.46)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes	Yes
First-stage F statistics		0.2	49.5	2.9	28.0
J-statstics p-value					0.51
$E[\Delta\text{lnP}]$	13.3	13.3	13.3	13.3	13.3
$E[\Delta\text{lnP}{:}(-\Delta L_{\text{p90}})\text{-}(-\Delta L_{\text{p10}})]$	-30.9	-245.1	-80.7	-101.5	-87
Observations	112	112	112	112	112

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; heteroskedasticity-consistent standard errors; firm-level controls are the firm's age, number of loans, amount of loans, loan spread, and loan maturity; and $\Delta\ln\tilde{P}_{\text{fg}}$ is the conventional part of the price index that excludes the variety-quality correction.

The discussion and three additional empirical analyses in this section suggest that the qualitative results in this article are robust to retail-level variations. In fact, these results suggest that the main estimated coefficients reported in Table 4 are likely to be the most conservative estimates because of incomplete pass-through. The 90th-10th percentile ratio is approximately 30% based on Tables 16 and 17, suggesting that the effect should be even larger once we control for retail-level variation. The extended model proposed in section 4.2 incorporates this dimension by allowing price rigidity and featuring incomplete pass-through at the retail level. Overall, I conclude that retail-level output price variation does not alter the main findings.

C.3 Demand Shocks

I implement two additional empirical analyses to show that the results are not driven by product demand shock. Given that an output price is an equilibrium object determined by demand and supply, one might be worried about the effect of a demand shock that could potentially confound the effect of the credit supply shock. In particular, the financial panic of 2008 is known to have originated in the housing market, which affects different parts of the economy. Influential papers such as Mian et al. (2013) use regional variation to document the strong effect of housing net worth on household consumption during this period, which would likely change output prices. If this type of local housing market disruption simultaneously affects local firms' credit conditions through local banks and makes firms decrease their output prices, then the estimated coefficients could be biased.

Although a product demand shock could be worrisome, I believe this factor plays a minor role in the main regression analysis. In fact, the presence of confounding factors, such as demand shock, is precisely why I use micro-level data, bank shock, and three different instruments. The general equilibrium effect arising from the housing market is apparent in the time series data, but the micro-level data allow me to avoid it by exploiting the differential effect of credit supply shock. Rather than using the conventional measures of financial constraint, I carefully construct and choose the bank shock and three different instruments to ensure that these credit supply shock measures are uncorrelated with the product demand shock. Empirically, I find that firms that face a negative credit supply shock increase their market share, as shown in Table 6. Because a negative product demand shock leads to a decrease in market share, these results show that the variation in the measure of the credit supply shock is not driven by the product demand shock.

To further demonstrate that the empirical results are not driven by the product demand shock, I allow detailed purchaser characteristics in the regression analyses as control variables and confirm the validity of the results. ACNielsen Homescan Panel data collect detailed household information such as income, education, employment, age, race, and household size. For example, once again consider Smucker's jam. I observe not only Smucker's price and quantity, its balance sheet, and its banking relationships but also its customer characteristics, including income and employment. I further combine zip-code-level housing price data from Zillow and country-level

Table 18: Effect of the Credit Crunch on the Output Price: Purchaser Characteristics

	(1)	(2)	(3)	(4)
	$\Delta\ln\mathrm{P}_{\mathrm{fg}}$: 2006q4-2007q2 to 2008q4-2009q2			
	OLS	IV	OLS	IV
		All		All
$(-\Delta L_f)$	-8.6***	-6.6***	-7.9***	-6.8***
	(1.0)	(1.9)	(1.0)	(1.9)
Initial purchaser char.	Yes	Yes	No	No
Change in purchasers' char.	No	No	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes
First-stage F statistics		207.8		205.2
J-statistics p-value		0.16		0.65
$E[\Delta\ln\mathrm{P}]$	11.3	11.3	11.3	11.3
$E[\Delta\ln\mathrm{P}$:$(-\Delta L_{\mathrm{p90}})$-$(-\Delta L_{\mathrm{p10}})]$	-18.7	-14.3	-17.1	-14.8
Observations	1673	1673	1673	1673

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, 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 $\Delta\ln\mathrm{P}_{\mathrm{fg}}$; purchaser characteristics are income, education, head of household employment, member of household employment, age, household size, housing price, home ownership, and Hispanic. All household characteristics are projection-factor-weighted averaged across households within a UPC, and sales-weighted averaged across UPCs within a firm-group; and Cragg-Donaldson F-stat is used for the first-stage F statistics.

homeownership data from the census. To construct firm-group-specific household characteristics, I first take a weighted average across households for a UPC by taking the sample weight of households as a weight. I then take a sales-weighted average across UPCs within the product group and the firm.

Table 18 reports the results with purchaser information. I include purchasers' income, employment, race, age, education, housing price, and home ownership—characteristics that are most likely to be affected by or sensitive to shocks during this period. The first three columns report the results with pre-Lehman purchaser characteristics, and the last three columns report the results with a change in purchaser characteristics. Regardless of the specifications, the estimated coefficients are negative and statistically significant with the purchaser characteristics. While the estimated coefficients of the household characteristics are not reported, most are not statistically significant. This result suggests that household characteristics are not key factors in explaining price dynamics if we use variation across firms and across product-groups instead of local variation.

I also confirm my results by allowing the state dimension in the data with state fixed

Table 19: Effect of the Credit Crunch on the Output Price: State Fixed Effects

	(1)	(2)	(3)	(4)	(5)
	$\Delta\ln\tilde{P}_{\text{fgs}}$: 2006q4-2007q2 to 2008q4-2009q2				
	OLS	$(-\Delta L_f)$ instrumented using			
		Lehman	ABX	BankItem	All
$(-\Delta L_f)$	-4.4***	-3.7**	-9.2***	-4.1*	-5.3***
	(0.9)	(1.9)	(3.5)	(2.4)	(1.8)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Product group FE	Yes	Yes	Yes	Yes	Yes
First-stage F statistics		23.90	13.30	13.30	12.70
J-statistics p-value					0.14
$E[\Delta\ln\text{P}]$	10.9	10.9	10.9	10.9	10.9
$E[\Delta\ln\text{P}$:$(-\Delta L_{\text{p90}})$-$(-\Delta L_{\text{p10}})]$	-10.1	-8.5	-21.2	-9.4	-12.3
Observations	26894	26894	26894	26894	26894

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, 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 a lagged dependent variable.

effects.[38] A concern in the main regression analysis is that some firms in the data operate only in particular regions that likely have different demand conditions. To address this concern, I compare products within the state by allowing and absorbing all state-level variation in the data. As shown in Table 19, I still find that firms that face a negative credit supply shock decrease their output prices. These results suggest that the main results in this article are robust to local factors, such as region-specific demand shocks.

C.4 Foreign Exposure

One concern regarding the regression analysis is a large change in the overall international exposure in this period. If those firms facing a large negative credit supply shock are the ones that particularly sell more to foreign countries or can hedge the risk by accessing foreign financial resources, the estimate might be biased. I proxy the foreign exposure of each company using their information on foreign subsidiaries and branches. Orbis records a number of subsidiaries and branches, and how many of them are in foreign countries. I measure foreign exposure by dividing a number of foreign subsidiaries by total subsidiaries and number of foreign branches by total branches and include these measures in the regression. As shown in Table 20, these variables do not seem to correlate with output price change, and the effect of credit supply shock on output price is robust to adding these control variables.

[38] Allowing state-group fixed effects, which absorb all state-group-level variation, does not alter the results.

Table 20: Effect of the Credit Crunch on Output Price: Foreign Exposure

	(1)	(2)	(3)	(4)	(5)
	$\Delta\ln\tilde{P}_{\text{fgs}}$: 2006q4-2007q2 to 2008q4-2009q2				
	OLS	$(-\Delta L_f)$ instrumented using			
		Lehman	ABX	BankItem	All
$(-\Delta L_f)$	-7.92***	-6.28*	-6.46**	-7.45**	-6.81***
	(1.61)	(3.76)	(3.01)	(3.60)	(2.33)
# of foreign subsidiaries	-6.16	-7.91	-7.72	-6.66	-7.34
	(4.61)	(5.62)	(5.59)	(6.10)	(5.11)
# of foreign branches	6.86	9.82	9.49	7.71	8.85
	(23.87)	(24.06)	(23.58)	(24.13)	(23.45)
firm-level controls	Yes	Yes	Yes	Yes	Yes
product group FE	Yes	Yes	Yes	Yes	Yes
First-stage F statistics		23.10	8.50	9.60	13.00
J-statstics p-value					0.96
$E[\Delta\ln\text{P}]$	11.4	11.4	11.4	11.4	11.4
$E[\Delta\ln\text{P}$:$(-\Delta L_{\text{p90}})$-$(-\Delta L_{\text{p10}})]$	-17.3	-13.7	-14.1	-16.2	-14.9
Observations	1658	1658	1658	1658	1658

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by firm and product group; weighted by initial sales; Firm-level controls: listed, 4-digit NAICS FE, age, size indicator, bond rating, number of loans, amount of loans, loan type, loan-year FE, multi-lead FE, number of loans due in post-Lehman FE, spread, maturity, lagged dependent variable

Table 21: Effect of the Credit Crunch on Output Price: Different Weightings

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\ln\mathrm{P}_{\mathrm{fg}}$: 2006q4-2007q2 to 2008q4-2009q2					
weight	Number of buyers			Number of UPCs		
	OLS		IV Lehman	OLS		IV Lehman
(-ΔL_f)	-2.44***	-9.68***	-7.63**	-2.24***	-5.59***	-6.59*
	(0.69)	(1.62)	(3.03)	(0.74)	(1.30)	(3.58)
firm-level controls	No	Yes	Yes	No	Yes	Yes
product group FE	No	Yes	Yes	No	Yes	Yes
First-stage F statistics			205.2			205.2
$E[\Delta\ln\mathrm{P}]$	12.5	12.5	12.5	12	12	12
$E[\Delta\ln\mathrm{P}$:(-ΔL_{p90})-(-ΔL_{p10})]	-5	-19.7	-15.5	-5.1	-12.7	-14.9
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; weighted by initial sales; firm-level controls are listed status, 4-digit NAICS FE, age, size indicator, bond rating, number of loans, amount of loans, loan type, loan-year FE, multi-lead FE, number of loans due in post-Lehman FE, spread, maturity, and a lagged dependent variable

C.5 Different Regression Weightings

In my main regression analysis, I used initial sales as a weight to give a larger weight to the firm-group that has larger sales. This regression matches the sales-weighted aggregate price index (Amiti and Weinstein (forthcoming)). Additionally, I used a different regression weight as a robustness and report the result in Table 21. First three columns use number of buyers as a weight, giving larger weight to the firm and group that matters the most for consumers. I also used the number of products in each bin as a weight, replicating the UPC-level regression. Regardless of the weighting, I find that firms facing a negative credit supply shock decrease their output prices relative to their counterparts.

C.6 Variants of ΔL_f

For my main regression analysis, I make a conservative choice in measuring credit supply shock by following Chodorow-Reich (2014) carefully. In this section, I conduct additional robustness checks using two variants of the measure of credit supply shock, ΔL_f.

First, in constructing a change in bank health at the bank level (leave-one-out), I use the change in a number of loans per bank to measure the credit supply shock, rather than the change in the amount of loans. Using number of loans helps to minimize the potential measurement error, but this choice might not capture the change in bank health properly if the majority of banks change their lending by decreasing the sizes of the loans (intensive margin), rather than the number of loans (extensive margin). While previous literature (Darmouni 2016) and Figure

Table 22: Effect of the Credit Crunch on Output Price: Variant of ΔL_f

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\ln\mathrm{P}_{\mathrm{fg}}$: 2006q4-2007q2 to 2008q4-2009q2					
	(-ΔL_f): Amount of Loans			(-ΔL_f): Average Bank Share		
	OLS		IV Lehman	OLS		IV Lehman
(-ΔL_f)	-5.2***	-21.5***	-22.7**	-6.9***	-18.3***	-44.7***
	(1.8)	(4.9)	(10.9)	(2.5)	(4.7)	(11.6)
firm-level controls	No	Yes	Yes	No	Yes	Yes
product group FE	No	Yes	Yes	No	Yes	Yes
First-stage F statistics			18.0			13.5
$E[\Delta\ln\mathrm{P}]$	11.4	11.4	11.4	11.5	11.5	11.5
$E[\Delta\ln\mathrm{P}$:(-ΔL_{p90})-(-ΔL_{p10})]	-11.3	-47	-49.5	-15	-40	-97.5
Observations	1658	1658	1658	1417	1417	1417

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by firm and product group; weighted by initial sales; firm-level controls are listed status, 4-digit NAICS FE, age, size indicator, bond rating, number of loans, amount of loans, loan type, loan-year FE, multi-lead FE, number of loans due in post-Lehman FE, spread, maturity, and lagged $\Delta\ln\mathrm{P}_{\mathrm{fg}}$; average bank share is the average bank share in the pre-Lehman period

2 show that the majority of the decrease in lending in this period is due to the extensive margin, I also confirm my results by using the amount of loans, which incorporates both intensive and extensive margins.

Second, to construct a firm-specific credit supply shock from a bank-specific change in bank health, I need a weight that measures the importance of each bank to a firm as firms typically deal with multiple banks in the syndicated loan market. In my main regression analysis, I used the last pre-Lehman loan—loans borrowed by firms from banks just before the Lehman failure—to maximize the effect of bank shock on firms. One concern of using the last pre-Lehman loan as a weight is that the measure relies on one particular loan. While this concern is not a first-order problem given the long-run bank-firm relationships that are prevalent in the United States, I reassure my results using the whole pre-Lehman period to construct the weight. I take an average across loans within firm and bank in measuring the weight.

Table 22 shows the results. The first three columns show the results based on the credit supply shock that utilize the amount of loans, and last three columns show the results based on the average bank share in the whole pre-Lehman period. Regardless of the measure of credit supply shock used, I still find that companies facing a negative credit supply shock decrease their output prices.

Table 23: Effect of the Credit Crunch on Output Price: Different Price Indexes

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\ln\mathrm{P_{fg}}$: 2007q4-2008q2 to 2008q4-2009q2					
	(-ΔL_f): 2006q4-2007q2, 2007q4-2008q2 to 2008q4-2009q2					
price index	Laspeyres		Paasche		Tornqvist	
	OLS	IV Lehman	OLS	IV Lehman	OLS	IV Lehman
(-ΔL_f)	-5.32***	-13.78**	-4.41***	-9.31**	-1.58**	-6.53**
	(1.69)	(5.77)	(1.26)	(4.60)	(0.79)	(3.27)
firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
product group FE	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F statistics		7.7		7.7		7.7
$E[\Delta\ln\mathrm{P}]$	3.18	3.18	2.6	2.6	1.52	1.52
$E[\Delta\ln\mathrm{P}$:(-ΔL_{p90})-(-ΔL_{p10})$]$	-11.6	-30.1	-9.6	-20.3	-3.5	-14.3
Observations	1617	1617	1617	1617	1617	1617

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by firm and product group; weighted by initial sales; firm-level controls are listed status, 3-digit NAICS FE, age, size indicator, bond rating, loan type, loan-year FE, multi-lead FE, number of loans due in post-Lehman FE, spread, and maturity; Using Lehman failure instrument directly as a measure of credit supply shock does not change the results.

C.7 Different Price Indexes

In my main regression analysis, I follow Hottman et al. (2016) and utilize the nested CES demand system to construct price index at the firm-group level. This formulation allows me to explicitly incorporate the change in product variety and quality and nests the model in Section 4 that uses the CES demand system.

In this section, I use more conventional price indexes to confirm that the main results do not depend on how the price indexes are constructed. I use three different indexes: Laspeyres, Paasche, and Tornqvist. To minimize the effect of entry and exit in products, I deliberately choose the period from 2007:Q4-2008:Q2 to 2008:Q4-2009:Q2 in measuring a dependent variable. Table 23 shows the results. Regardless of which index is used in the regression analysis, I still find that companies facing a negative credit supply shock decrease their output prices. While the first-stage F-statistics is smaller than 10, using the instrument directly as a measure of the credit supply shock does not change the result.

C.8 Testing the Selection of Unobserved Variables

In this section, I additionally support my identification assumption by conducting a test originated from Khwaja and Mian (2008) and implemented in Chodorow-Reich (2014). This test is to check whether there is an unobserved variable that might bias the estimate in the main regression.

Table 24: Testing the Selection of Unobserved Variables

	(1)	(2)
	Δ ln(Loans)	
ΔBank Health$_{\text{-f,b}}$	9.76**	9.53**
	(4.43)	(4.72)
firm-level controls	No	Yes
naics 3-digit FE	No	Yes
Borrower FE	Yes	No
Observations	402	402
R^2	0.695	0.599

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by borrower and lender; firm-level controls are listed status, 4-digit NAICS FE, bond rating, number of loans, amount of loans, loan type, loan-year FE, multi-lead FE, number of loans due in post-Lehman FE, spread, and maturity

Consider the following regression analysis:

$$\Delta \ln(\text{Loans}_{fb}) = \lambda_f + \gamma \Delta(\text{Bank Health})_{\text{-}f,b} + \varepsilon_{fb} \tag{C.1}$$

where f is firm, b is bank, Loans$_{fb}$ is the amount of loans received by firm f from bank b, Δ(Bank Health)$_{\text{-}f,b}$ is the leave-one-out change in bank health I measured in section 3.1, and λ_f is a firm fixed effect. In this regression, the coefficient γ refers to how the amount of loans received by firm f from bank b changes when their bank health deteriorates.

The test is to look at the stability of the coefficient (γ) by including and excluding the firm fixed effect (λ_f). Including the firm fixed effect implies that I look at the effect of bank shock on loan amount *within* the firm. That is, for a given firm, how do loans received by this firm change when its banks can no longer lend to it. Since there is no variation across firms, this regression analysis is not subject to concern arises from the fact that different firms might demand credit differently. On the other hand, excluding firm fixed effect implies that I use variation across firms in estimating the coefficient γ. In this case, if it is true that different firms demand credit differentially, the coefficient would be biased and different from the estimates with firm fixed effect.

Table 24 shows the estimated coefficient with and without firm fixed effects. Column (1) reports the estimated coefficient when I allow firm fixed effects, and column (2) reports the estimated coefficient when I do not allow firm fixed effects but instead allow firm-level control variables. As one can see, the estimated coefficient is stable across two different specifications; a decrease in one standard deviation of a change in bank health leads to a decrease in the amount of loan received by the firm by about 9.5 9.8 percent. This result suggests that the unobserved characteristics of firms are not likely to be correlated with the credit supply shock measure I constructed conditioning on observed characteristics.

D Liquidity Position

In the main text, I discuss how previous works in corporate finance, such as Almeida et al. (2014), Kahle and Stulz (2013), and Bates et al. (2009) raise concerns about using liquidity position as a measure of financial constraint. I already report and confirm the results of Kahle and Stulz (2013) in Table 6 by showing that companies facing a negative credit supply shock increase their liquidity.

In this section, I present three additional analyses to confirm the results in Bates et al. (2009) and to understand why different measures of financial constraint—bank shock and liquidity—lead to different pricing behaviors of firms. First, I replicate the regression in Bates et al. (2009) by using the Compustat database. In particular, I used only the year 2006 to compare how those firms that had a large amount of cash holdings are different compared to those firms that had a small amount of cash holdings before the financial panic. Consider the following regression analysis:

$$\text{liquidity}_{i,\text{t}} = \beta_0 + \beta X_{i,2006} + \epsilon_{i,2006} \tag{D.1}$$

where t = {2006, 2008}. Liquidity is $\frac{\text{cash + cash equivalent assets}}{\text{total assets}}$ that is used in Bates et al. (2009) and Gilchrist et al. (2017), and X_i is a vector of firm-level characteristics. The firm-level characteristics used in this regression are cash flow volatility,[39], debt to assets, capital expenditure to assets, acquisition to assets, firm size, market to book ratio, networking capital to assets, cash flow volatility, dividend dummy, and R&D to sales.

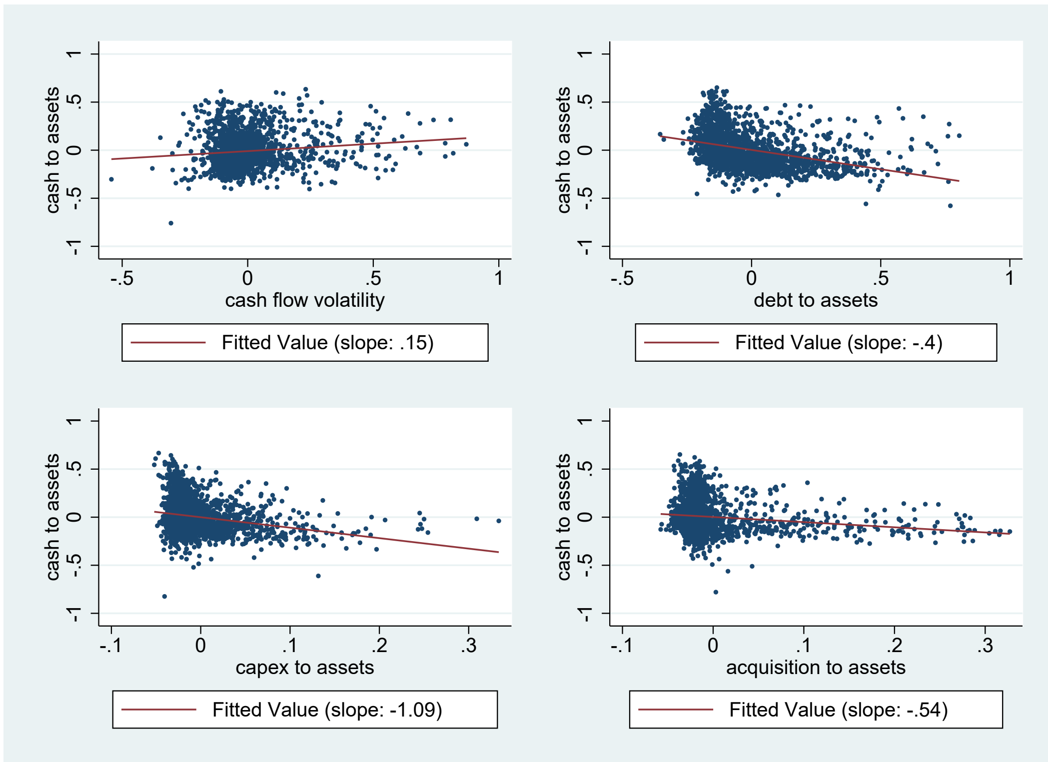
Figure 9 graphically shows the regression results when I compare firms based on their 2006 liquidity position. Standard errors are omitted for visibility, but all the coefficients are statistically significant at the 5% level.[40] The results show that firms that had a large amount of liquidity in 2006 had higher cash flow volatility, and borrowed more, invested more, and spent more money to acquire more firms in 2006. These characteristics are likely to reflect financially constrained firms, rather than financially unconstrained firms. This analysis, which is a replication of Bates et al. (2009) using the year 2006, is consistent with the survey paper by Almeida et al. (2014), who argue that companies hold more cash when they are more likely to be financially constrained.

Additionally, I regress 2008 firm-level characteristics on 2006 liquidity to see how those firms that had high initial liquidity reacted during the financial panic of 2008. Under the assumption that the financial shock that directly hits companies is the dominant shock in the U.S. economy during the 2007-09 recession, weak liquidity position might be a good measure of financial constraint as those firms that initially had a small amount of liquidity are likely to suffer more from the financial shock. In this case, those firms with a small amount of initial liquidity would react as if they are financially constrained during the 2007-09 recession. In fact, this idea is very

[39]Following Bates et al. (2009), cash flow volatility is measured by taking the standard deviation of cash flow for the previous 10 years, requiring at least three observations per firm.

[40]Regression table is available upon request.

Figure 9: Firm Characteristics in 2006 and Cash Holdings in 2006



Note. There are a total of 1707 firms; the dependent variable is liquidity (cash to assets), and independent variables are cash flow volatility, debt to assets, capital expenditure to assets, acquisition to assets, firm size, market to book ratio, networking capital to assets, cash flow volatility, dividend dummy, and R&D to sales. The plots report the estimated coefficients of the selected firm-level characteristics, which are cash flow volatility, debt to assets, capital expenditure (capex) to assets, and acquisition to assets. These plots represent the correlation between liquidity (cash to assets) and firm characteristics after partialling out other characteristics based on the Frisch-Waugh-Lovell theorem.

Table 25: Firm Characteristics in 2008 and Cash Holdings in 2006

	(1)	(2)	(3)	(4)
	cash flow volatility	capex to assets	acquisition to assets	debt to assets
cash to assets (2006)	0.25***	-0.04***	-0.01**	-0.32***
	(0.03)	(0.01)	(0.00)	(0.05)
2-digit sic	No	No	No	No
R^2	0.12	0.02	0.00	0.12
obs	2638	3062	2962	2920
	(5)	(6)	(7)	(8)
	cash flow volatility	capex to assets	acquisition to assets	debt to assets
cash to assets (2006)	0.21***	-0.02**	-0.01***	-0.28***
	(0.04)	(0.01)	(0.00)	(0.04)
2-digit sic	Yes	Yes	Yes	Yes
R^2	0.17	0.30	0.04	0.22
obs	2635	3059	2959	2917

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by sic 2-digit code.

similar to what I did with the bank shock. I argue that those companies with a small amount of initial liquidity are likely to be more sensitive to the bank shock, and I show the empirical support for this in Table 7.

As shown in Table 25, however, I still find that those firms that had a small amount of liquidity in 2006 had a stable cash flow, invested more, borrowed more, and spent more money to acquire firms in 2008 compared to firms that had a large amount of liquidity in 2006. These results are true regardless of whether I allow 2-digit SIC fixed effects as reported in columns (5)-(8). These results suggest that the Great Recession itself does not capture the bank shock, or "financial shock" in general, and liquidity position does not precisely measure the level of financial constraint even we interact it with the Great Recession. In this period, there are many other events happening at the same time, such as decreases in the housing price (Mian and Sufi (2014)), oil price (Hamilton (2009)), and international trade (Eaton et al. (2016)), making it difficult to utilize the Great Recession as an aggregate financial shock.

Lastly, I re-estimate Equation 3.9 by controlling for the initial liquidity position and report the results in Table 26. Columns (1)-(3) use the average liquidity across 2006-07, and columns (4)-(6) use the liquidity position in 2006. Without allowing the firm-level initial and lagged characteristics as in column (1) and (4), it seems that both bank shock and initial liquidity position independently explain output price dynamics. After adding other firm-level control variables, however, the coefficient of bank shock becomes larger and statistically significant, whereas the coefficient of initial liquidity position changes sign and becomes statistically non-significant. These results support the views that the initial liquidity is highly correlated with other characteristics of firms and cannot precisely measure the financial constraint.

Table 26: Firm Characteristics in 2008 and Cash Holdings in 2006

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\text{lnP}_{\text{fg}}$: 2006q4-2007q2 to 2008q4-2009q2					
	OLS		IV (-ΔL_f)	OLS		IV (-ΔL_f)
			All			All
(-ΔL_f)	-2.26***	-4.54***	-5.83**	-2.21***	-4.12***	-5.75**
	(0.85)	(1.52)	(2.46)	(0.83)	(1.26)	(2.31)
$\overline{\left(\frac{\text{cash}}{\text{total asset}}\right)}_{2006\text{to}07}$	-1.04	7.96	9.51			
	(2.92)	(9.34)	(10.58)			
$\left(\frac{\text{cash}}{\text{total asset}}\right)_{2006}$				-2.18*	5.37	5.48
				(1.15)	(6.32)	(6.93)
firm-level controls	No	Yes	Yes	No	Yes	Yes
product group FE	No	Yes	Yes	No	Yes	Yes
First-stage F statistics			5.2			6.2
J-statstics p-value			0.27			0.12
$E[\Delta\text{lnP}]$	11.53	11.53	11.53	11.53	11.53	11.53
$E[\Delta\text{lnP}$:(-ΔL_{p90})-(-ΔL_{p10})]	-4.78	-9.61	-12.35	-4.68	-8.72	-12.17
Observations	1318	1318	1318	1318	1318	1318

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by firm and product group; weighted by initial sales; firm-level controls are listed status, 4-digit NAICS FE, age, size indicator, bond rating, number of loans, amount of loans, loan type, loan-year FE, multi-lead FE, number of loans due in post-Lehman FE, spread, maturity, and lagged $\Delta\text{lnP}_{\text{fg}}$

Table 27: Main Result: With Dummy Variable

	(1)	(2)	(3)
	$\Delta\ln\mathrm{P_{fg}}$: 2006q4-2007q2 to 2008q4-2009q2		
	OLS	($-\Delta L_f$) instrumented using	
		Lehman	All
D_f	-13.81***	-15.09**	-14.74***
	(2.78)	(7.03)	(4.24)
firm-level controls	Yes	Yes	Yes
product group FE	Yes	Yes	Yes
First-stage F statistics		10.20	8.10
J-statstics p-value			0.58
$E[\Delta\ln\mathrm{P}]$	11.4	11.4	11.4
Observations	1658	1658	1658

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by firm and product group; weighted by initial sales; firm-level controls are listed status, 4-digit NAICS FE, age, size indicator, bond rating, number of loans, amount of loans, loan type, loan-year FE, multi-lead FE, number of loans due in post-Lehman FE, spread, maturity, and lagged $\Delta\ln\mathrm{P_{fg}}$

E Calibration: Regression with a Dummy Variable

In this section, I show the regression results I used to calibrate the magnitude of the shock parameter. I cannot directly use my estimated coefficient in Table 4, as I use a continuous measure of credit supply shock, whereas my model features two identical representative entrepreneurs with different degrees of credit supply shock. To match the model with the data, I define a dummy variable that equals 1 if the credit supply shock measure is greater than its median value and 0 otherwise:

$$D_f = \begin{cases} 1, & \text{if } \Delta L_f \geq \text{median}(\Delta L_f) \\ 0, & \text{otherwise} \end{cases}$$

I rerun the main regression analysis (Equation 3.9) by replacing the credit supply shock measure with the dummy variable above:

$$\Delta \ln P_{fg} = \lambda_g + \beta D_f + \theta X_f + \varepsilon_{fg} \tag{E.1}$$

In this way, I can directly match my model where half of the producers face a negative credit supply shock, and the other half does not. Table 27 shows the results. The estimated coefficient is about -15%. I calibrate the magnitude of the credit supply shock to the representative entrepreneur 1 so that the decrease in relative price is 15%.