Inflation, Inventory, and Credit Market Disruptions: Micro-level Evidence and Aggregate Implications*

Ryan Kim†

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Preliminary‡

Abstract

I am studying how a credit crunch affects output price and inventory dynamics. I exploit the unique micro-level data and the change in bank health at the time of the Lehman failure as a quasi-experimental identification strategy to find that credit-constrained firms *decreased* their output price by approximately 15% relative to their unaffected counterparts. I hypothesize that credit-constrained firms drop their price by liquidating their inventory to generate extra cash flow and provide strong empirical supports for this hypothesis. I integrate this micro-level study into the business cycle model by explicitly allowing two identical groups of producers facing different degrees of credit supply shock. While credit-constrained firms have the incentive to increase their price due to the "pass-through" of credit costs, they indeed decrease their price as the "fire-sale" of the inventory mechanism dominates this effect. This finding sheds light on the fluctuation of inflation, inventory, and other aggregate variables.

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†Ryan (Sung Ryong) Kim sk3669@columbia.edu. Economics Department, Columbia University

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1 Introduction

The question of how and to what extent credit market disruptions affect the whole economy has been a vital interest in macroeconomics and finance literature, particularly after the 2007-09 financial crisis. This period is characterized by not only a significant fall in total output and employment but also a dysfunctional credit market. In the peak of the credit market stress following the Lehman Brothers failure in September 2008, the new loans to large borrowers dropped by 79% relative to the credit boom period (Ivashina and Scharfstein 2010). The TED spread, which is an indicator of perceived credit risk, exceeded 300 basis points right after the Lehman Failure, breaking the previous record set after the Black Monday crash of 1987.

Precisely at the time of these credit market disruptions, the producer price index plummeted by about 15% in three months (figure 1b). Given this aggregate correlation, this project seeks to answer the following questions: Do credit-constrained firms decrease their output price? If so, why? What are the aggregate implications?

[Figure 1 about here.]

I first establish that credit-constrained firms decrease their output price by approximately 15% more compared to their unaffected counterparts using a unique micro-level data and quasi-experimental identification strategy. While there is a clear positive correlation between inflation and credit in figure 1a and 1b, it is extremely hard to identify the true relationship between these two series solely based on the aggregate data. Many different episodes are happening at the same time, such as a fall in housing price (Mian et al. 2013), oil price (Hamilton 2009), and international trade (Eaton et al. 2016), which makes aggregate time-series comparison nearly impossible. Therefore, I build up the novel micro-level data by combining producers' variety-quality-adjusted price index with their relationship with the banks. Then I exploit the change in bank health due to the Lehman failure as an exogenous variation on producers to overcome the identification challenge. Figure 1c graphically illustrates this analysis.

I hypothesize that credit-constrained firms decrease their price by liquidating their inventory to generate extra cash flow and provide strong empirical supports of this hypothesis. I first show that, at the time of the Lehman bankruptcy, there was an enormous decline in aggregate inventory as well as a fall in output price index (figure 1d). Then I again utilize the micro-level data and the corresponding identification strategy to find that credit-constrained firms temporarily decrease their inventory and also increase their market share relative to their counterparts, confirming this hypothesis.

I integrate this micro-level study in the business cycle model to formalize the empirical analysis and discuss the aggregate implications. I allow two identical groups of producers facing different degrees of credit supply shock to explicitly reflect the micro-level analysis. Producers in this model hold inventory to avoid stock-out arising from product-level idiosyncratic demand shock. The exogenous decrease in one group of firms' borrowing capabilities makes these firms quickly liquidate their inventories by dumping their products at a low price to generate extra cash flow. This "fire-sale" effect is powerful enough to dominate the "pass-through" effect of credit costs on output price under the standard calibration, leading the credit-constrained firms' price to fall in the short-run. Only by including the fire-sale of inventory into the model does the adverse credit supply shock explain the *aggregate* inflation and inventory dynamics after the Lehman failure. The model also does a good job in explaining the other main aggregate variables, such as employment and investment, due to the negative credit supply shock. At the same time, the model captures a relative decrease in output price and inventory and a relative increase in market share due to the negative credit supply shock, consistent with the micro-level evidence.

The findings in this project are surprising as these seemingly contradict the influential work by Gilchrist et al. (forthcoming), who find, with the other micro-level data, that financially-constrained firms *increase* their output price. I reconcile two results by first establishing that the difference in results comes from the difference in the *types* of the financial constraint, which is the firms' cash holding in Gilchrist et al. (forthcoming). Using their financially-constrained measure in my sample, I replicate their empirical finding that cash-constrained firms increase their output price. I further show that my results are robust to the inclusion of the cash-constrained measure, and also that the credit-constrained and cash-constrained measures are negatively correlated. These findings suggest that cash-constrained firms and credit-constrained firms behave oppositely regarding their output price decision, and it is important to distinguish the type of financial shock in studying the output price dynamics. This is an important future research area but not a focus of this paper.

There are other papers such as Del Negro et al. (2015) and Christiano et al. (2015) that study how financial friction affects inflation in the business cycle framework. These papers rely on the cost channel of a financial shock to explain the inflation dynamics, and the theoretical results in this article are consistent with their results if I do not incorporate the inventory in the model. I seek to expand these previous studies by bringing in a "fire-sale" of inventory mechanism to be consistent with the micro-level empirical evidence I find in this article. Papers in Industrial Organization and Corporate Finance also study this topic, but it is still inconclusive how financial distress affects output price, particularly at the aggregate level. Some papers find that financial distress leads to decrease in output price based on airline industries (Borenstein and Rose 1995, Phillips and Sertsios 2013), while others find the opposite results based on retail industries (Chevalier 1995a, Chevalier 1995b, Chevalier and Scharfstein 1995, Chevalier and Scharfstein 1996).

Concerning the empirical analysis, this paper draws upon the methodologies used in Chodorow-Reich (2014) and Hottman et al. (2016). I use the same identification strategy used in Chodorow-Reich (2014), but answer a different question with different data. In constructing firm-group-level price index from the scanner level barcode data, I adopt the nested-CES demand system used in Hottman et al. (2016) to adjust for the variety and quality effect. Regarding the theoretical analysis, main ingredients of my model are based on Iacoviello (2005) but I add stock-out avoidance motive of inventory holding as in Wen (2011) to reflect my hypothesis and the micro-level empirical evidence in the model.

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

2 Micro-level Data

A major novelty of this paper is to construct a micro-level data that integrates information on producers' output price and their relationship with banks.

A producers' price data comes from the ACNielsen Homescan Panel, made available by the Kilts Marketing Data Center at University of Chicago Booth School of Business. The data contains millions of barcode-level products price weekly recorded from on average 55,000 households a year. Nielsen assigns a sample weight to each household based on ten different demographic variables to make the sample nationally representative. They cover about 30 percent of all household expenditure on products in CPI.

There are many advantages in using ACNielsen database to identify the effect of credit supply shock on output price dynamics. First, it records product price at barcode-level, which is likely to be the most granular way to define the product. This feature helps to capture the effect of introduction and destruction of products on inflation, which is known to be significant (Bernard et al. 2010, Broda and Weinstein 2010, Nakamura and Steinsson 2012). It also allows comparing a change in product price across credit-constrained firms and their counterparts within a very detailed category. Besides, this data records other information such as product sales, unit, size, purchasers' characteristics, location, and retail store where the product was purchased. This information is valuable to address other potential identification concerns such as the effect of a change in taste or quality (Hottman et al. 2016), purchasers' income and housing price (Mian et al. 2013), and retailers' behavior (Nakamura 2008) on output price.

I access the GS1 Data Hub, Orbis, and Fixed Income Security Database (FISD) to combine barcode-level data and its producers' information. GS1 is the company that issues a barcode to producers.[1] Their data records company name and full address for each barcode-level product. I use their data to link barcode-level product information with its producer information in Orbis data. Orbis is the firm-level data made by Bureau van Dijk and has detailed administrative, financial, production and ownership information for both public and private firms. I further merge this data with FISD, which records historical corporate bond issuance and rating, to extract information on producers' bond market assessment.

Lastly, I combine Dealscan database to extract information on bank lending to each producer. Dealscan database contains comprehensive historical information on loan pricing and contracts details, terms, and conditions. It mainly includes information in the syndicated loan market, where more than one bank arranges the loan to firms. They capture between half and three-quarters of the volume of outstanding commercial and industrial loans in the US (Carey and Hrycay 1999). I supplement this data with Zillow housing price and Current Population Survey (CPS) home-ownership data to specifically address a drop in housing price at this period. I also supplement other variables that reflect a change in bank health used in Chodorow-Reich (2014).

[1] 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 per bar code cost for firms purchasing larger numbers of them (see http://www.gs1us.org/get-started/im-new-to-gs1-us)

3 Micro-level Empirical Analyses

This section analyses the effect of credit market stress on output price and inventory dynamics with the micro-level data discussed in the previous section. I first discuss the construction of firm-group-specific variables, regression specification, and the empirical result that credit-constrained firms decrease their price. Then I propose an explanation why credit-constrained firms lower their price and provide empirical supports based on the inventory and market share regression.

3.1 Credit Supply Shock (ΔL_f)

I follow Chodorow-Reich (2014) carefully to construct the ΔL_f, credit supply shock measure. This measure extracts information on a change in firms' access to credit as a consequence of a change in bank health in a simple and coherent way.

I choose two period, pre- and post-Lehman, to exploit the Lehman failure happened on September 2008 in measuring the credit supply shock. The post-Lehman period is three-quarters that start right after the Lehman failure: 2008Q4-2009Q2. At this time, a number of loans issued, which is used to measure the credit supply shock, dramatically decreased, and interest spread spiked up to a great extent (figure 2). The pre-Lehman period corresponds to the same quarters in earlier years, at the time of the credit market expansion: 2005Q4-2006Q2 and 2006Q4-2007Q2.

[Figure 2 about here.]

Based on this timing, I first measure the change in bank health from the number of loans they made across pre- and post-Lehman period as follow:

$$\Delta(\text{Bank Health})_{-f,b} = \frac{\sum_{j \neq f} \alpha_{jb,\text{post}} \times \mathbb{1}(\text{b lent to j in post-Lehman})}{\frac{1}{2}\sum_{j \neq f} \alpha_{jb,\text{pre}} \times \mathbb{1}(\text{b lent to j in pre-Lehman})} \tag{3.1}$$

where $\mathbb{1}()$ is an indicator variable equals to 1 if what is in parenthesis is true and 0 otherwise. α_{jbt} denotes the bank b's share of the total amount of loan for each syndicated loan it made to firm j in period t.[2]

Roughly, the above measure captures a number of loans made by bank b in the post-Lehman period over a number of loans made by bank b in the pre-Lehman period. However, there are two additional complications. First, I multiply α_{jbt} for each loan made by bank b to firm f to reflect

[2] Dealscan database only reports about one-third of α_{jbt} among total loans. I impute missing α_{jbt} by using the same method as in Chodorow-Reich (2014).

the importance of each loan. The multiplication is due to the structure of the syndicated loan, where various banks arrange one loan to a borrower. Some banks have a larger share of loans compared to other banks, and I reflect this difference when I aggregate a number of loans issued in each period. Second, I intentionally omit the firm f in the summation to ease the concern on credit demand shock. In this way, firm f's loan made by bank b is not used to construct credit supply shock to firm f.

As a second step, I construct the credit supply shock faced by borrower f using the weighted average of the change in bank health measure.

$$\Delta L_f = \sum_{b \in S_f} \alpha_{fb,\text{last}} \Delta(\text{Bank Health})_{-f,b} \tag{3.2}$$

The weight $\alpha_{fb,\text{last}}$ is bank b's share of the total amount of loan for the last syndicated loan it made before the Lehman failure. This weight reflects the importance of each bank for each firm right before the collapse of the Lehman Brothers.

While the variable above provides a simple and clean way to measure the credit supply shock arises from the change in bank health, the loan demand channel might reflect some of the variation in this variable. To address this concern, I use three instruments that are used in Chodorow-Reich (2014): Lehman exposure to banks, Banks' asset-backed securities holding, and bank statement items that are not likely to be correlated with borrowers' characteristics. The correlation among these three variables are weak at the firm-level and likely to generate independent exogenous variation on producer's credit supply.[3]

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

I follow Hottman et al. (2016) to build up a firm-group-specific price index from the ACNielsen Homescan Panel database. This framework uses a nested-CES demand system that explicitly addresses the effect of variety and quality on output price. Another advantage of this demand structure is its consistency with the model I propose in section 4.

Consider the following utility function

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

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

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

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

where subscript f is firm, u is UPC or barcode-level product. Ω_{gt} is the set for the firms within product group g at time t, and Ω_{fgt} is the set for the UPC made by firm f in group g at time t. φ_{fgt} captures perceived quality for each firm f within group g at time t, and φ_{ut} captures the perceived quality for each UPC 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.[4]

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 share of products are[5]

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

The above equation makes clear how this framework perceives UPC-specific and firm-specific quality, φ_{ut} and φ_{fgt}. These are what changes the market share holding price fixed. That is, if two products have the same price but one product has a larger market share compared to the other product, this product has a higher perceived quality compared to the other product in this setup.

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

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

[5] This can be recovered by using the Shephard's Lehmma.

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

where $\tilde{S}^U_{fgt} = \left[\prod_{u\in\Omega^U_{fgt}} S^U_{ut}\right]^{\frac{1}{N^U_{fgt}}}$, the geometric average of market share of UPC by firm f within group g at time t. Plug in (3.7) into (3.5), one can derive the following firm-group-time price index

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

where the first term is the geometric average of UPC-level price within firm and group. This is analogous to the standard price index, such as Tornqvist or Laspeyres index. The second term is the variant of Theil index, which captures quality and variety correction. Note that $\sum_u \frac{S_{ut}}{\tilde{S}_{fgt}}$ in the second term increases if (1) a number of UPCs made by firm f within group g (N_{fgt}) goes up (variety effect), or UPC share dispersion within firm goes up (quality effect)[6].

I use estimated σ^U_g from Hottman et al. (2016) to recover price index in (3.8).[7] Since t is at quarterly frequency, I take a geometric average across quarters within 2006q4-2007q2 (last three-quarters in pre-Lehman period) and 2008q4-2009q2 (post-Lehman period) to make it comparable to the period of the credit supply shock. Then I take a difference of logged price index across two periods to construct the dependent variable.

3.3 The Effect of Credit Crunch on Output Price

I examine the effect of credit supply shock on producers' output price dynamics with 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 firm, g is product group or category. P_{fg} is the firm-group specific price index I constructed from the ACNielsen barcode-level data. ΔL_f measures the change in firm-level credit supply as a result of the deterioration of their bank health. X_f captures initial and lagged

[6] UPC share dispersion reflects the quality or appeal. To illustrate this, consider the following two different scenarios. In both scenarios, consumers face two products (same number of products) that have the same price but very different quality for scenario 1 and the same quality for scenario 2. In this case, scenario 1 is better for consumers as they can choose what they like among these products (high-quality product for their taste).

[7] I am very grateful to authors for providing me these estimates.

firm-level control variables. λ_g is allowed in the regression to compare price *within* product groups. β is the coefficient of interest that captures how much bank liquidity shock affects a firm's decision to change its price.

I control for rich observable firm-level characteristics (X_f) in this regression to address potential spurious correlation. To control for firms' liquidity substitution from loan market to bond market when banks' cannot lend a loan (Becker and Ivashina 2014), I include Pre-Lehman bond rating and issuance for each firm. The fixed effects of 4-digit NAICS industry, listed status, age, and size indicator of firms are included to compare firms within these categories. To address the differential degree of loan market access for each firm, I control for a number and amount of loans firms received in the pre-Lehman period. I also control a number of loans due in the post-Lehman period as firms would suffer more if they need to pay out their loan in the post-Lehman period. Furthermore, I control for the type of the last loan (term loan vs. revolver/line), the year the last loan is issued, whether firms dealt with multiple lead banks, and last loans' spread and maturity to make a reliable comparison between credit-constrained and unconstrained firms.

Table 1 shows the empirical result based on the equation (3.9). I change the sign of ΔL_f to interpret β as a result of *negative* credit supply shock on output price. Both OLS and IV regression gives a consistent qualitative result. Quantitatively, increase in one standard deviation of negative credit supply shock decrease output price by about $15 \sim 18\%$.

[Table 1 about here.]

3.4 Mechanism: "Fire-sale" of Inventory

This result in the previous section is seemingly counter-intuitive as all of the earlier studies that I aware predict the opposite. Many of past papers think of financial distress as an increase in credit cost, hence predicts an increase in price due to a negative credit supply shock.[8]

I propose a hypothesis that can rationalize the empirical finding: "fire-sale" of inventory. When firms are credit-constrained and cannot borrow, they have an incentive to liquidate their inventory to generate extra cash flow quickly. At the aggregate level, it is evident inventory

[8]Examples of articles 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). There are other mechanisms discussed in the previous literature. For example, Gilchrist et al. (forthcoming) put more emphasis on the consumer habit and Chevalier and Scharfstein (1996) emphasizes the strategic interaction in explaining firms' price setting behavior due to the financial friction.

dramatically decreased after the Lehman failure (figure 1d), but it is hard to conclude based on this correlation. Thus, I provide empirical supports for this hypothesis by using the same micro-level data and identification strategy I employed in the previous section.

I use the following regression specification:

$$g_f^{\text{Inv}} = \beta_0 + \gamma \Delta L_f + \theta X_f + \varepsilon_f \tag{3.10}$$

where g_f^{Inv} is the inventory growth, ΔL_f is the credit supply shock constructed in the earlier section, and X_f is firm-level control. Also, I run the same regression as in the equation (3.9), but using a product market share as an independent variable instead of the output price index.

I find that credit-constrained firms decrease their inventory and increase their market share relative to their counterparts as in Table 2 and the Table 3. The decline in inventory happens for the short-run, reflecting that credit-constrained firms cannot sell inventory forever. This result confirms the hypothesis that credit-constrained firm decreases their inventory to generate additional revenue from the product market.

[Table 2 about here.]

[Table 3 about here.]

3.5 Additional Analyses and Robustness

This section presents additional regression analyses and robustness checks.

3.5.1 Financial Shock: Firms' Cash Holding vs. Change in Bank Health

As discussed earlier, the results in this paper look opposite to the result in Gilchrist et al. (forthcoming). However, this article is sharply different from their paper and answers distinct questions. This article looks at how a change in bank health after the credit crunch affects output price dynamics, whereas Gilchrist et al. (forthcoming) look at how firms' initial cash position affects output price.

To emphasize this difference, I first find that cash-constrained firms increase their price in my sample, consistent with the results in Gilchrist et al. (forthcoming). Consider the following regression specification:

$$\Delta \ln P_{fg} = \lambda_g + \gamma \text{LIQ}_f + \theta X_f + \varepsilon_{fg} \tag{3.11}$$

where LIQ_f is either initial cash holding or change in cash holding. As reported in Table 4, even in my sample, initial cash scarce firms (or firms that decrease their cash) increase their output price relative to their counterparts.

[Table 4 about here.]

Given the above results, there is an interesting but separate question of how cash holding and credit supply shock interact in firms' output price decisions. While this is not the main issue I study in this paper, I conduct three additional analyses to partially address this question.

I first find that a decrease in cash holding and the negative credit supply shock measure I used in this paper are negatively correlated (Table 5).[9] Given this correlation, it is not surprising that this paper finds a different result compared to Gilchrist et al. (forthcoming). One possible explanation of this negative correlation is the endogeneity of a change in cash holding with respect to the negative credit supply shock. As emphasized in liquidity management studies (Almeida et al. 2014), when firms face financial constraints, they hold more liquidity to ensure efficient investment in the future. In this case, credit-constrained firms, which increases their cash holding due to this precautionary motive, decrease their price based on the "fire-sale" of inventory mechanism emphasized in this paper. Based on this explanation, this work and Gilchrist et al. (forthcoming) are fully consistent with each other regarding the relationship between a change in price and a change in cash holding.[10]

[Table 5 about here.]

Concerning the other measure used in Gilchrist et al. (forthcoming), the initial cash holding, I find that my results are robust to the inclusion of this measure as shown in Table 6.[11] The credit supply shock and the initial cash holding seem to generate somewhat independent variation on a change in output price without control variables. While a coefficient of the initial cash holding changes the sign and becomes statically insignificant with other control variables, it is

[9] I find a near zero correlation between the initial cash holding and the negative credit supply shock.

[10] Ideally, I want to use an instrument to isolate the exogenous variation in a change in cash holding. Unfortunately, I do not have a good instrument to do this analysis. I cannot use a credit supply shock measure I constructed as this violates the condition that the instrument affects a change in output price only through a change in cash holding. It is because a credit supply shock affects output price also through a change in inventory, which is the mechanism I discussed extensively in this project. I also put both a change in cash and inventory as independent variables and use multiple instruments to run this regression, but instruments are not powerful enough to estimate parameters consistently in this case.

[11] I do not include a change in cash holding as it is likely to be an outcome of the negative credit supply shock.

hard to conclude the true relationship between initial cash holding and a credit supply shock solely based on this regression analysis.[12]

[Table 6 about here.]

Besides, I run another regression to show that my analysis is not contradictory to Gilchrist et al. (forthcoming) regarding the initial cash holding measure. Suppose a small initial cash holding measures financial constraint as discussed in Gilchrist et al. (forthcoming) and credit-constrained firms decrease their output price as shown in the previous section of this article. In this case, small initial cash holding firms can increase their output price but those firms with credit constraint must decrease their price. I use the following specification to check this possibility:

$$\Delta \ln P_{fg} = \gamma_1 \mathrm{D}_{f,(\mathrm{cash}_{t_0} < \mathrm{cash}_{t_0,p50})} \times \Delta \mathrm{L}_f + \gamma_2 \mathrm{D}_{f,(\mathrm{cash}_{t_0} < \mathrm{cash}_{t_0,p50})} + \theta \Delta \mathrm{L}_f + \theta_3 X_f + \lambda_g + \varepsilon_{fg}$$

[Table 7 about here.]

As shown in Table 7, while small initial cash holding firms increase their output price, small initial cash holding firms with credit constraint decrease their output price compared to those without credit constraint. These regression results highlight that my paper is answering a different question compared to the Gilchrist et al. (forthcoming) as we are using a different independent variable: initial cash holding and credit supply shock.

By comparing this paper with Gilchrist et al. (forthcoming), this section shows the importance of differentiating the types of financial shock in studying firms' output price dynamics. This will be an important and interesting future research area.

3.5.2 Decomposition of Price Index

The nested-CES demand system is not only useful to construct the variety-quality adjusted price index but also allows separating the price index into a conventional price index and the variety-quality correction term. In this way, I can run a separate regression for each part to see how credit supply shock affects output price.

[12] One possible explanation is based on the endogeneity concern about the initial cash holding, just like a change in cash holding. It could be that firms that hold more cash in the beginning are the ones that are financially constrained compared to the firms with small initial cash holding (Almeida et al. 2014). Or, it could be that this initial cash holding measure does not measure the financially constraint. Farre-Mensa and Ljungqvist (2016) document that this type of firm-level liquidity measures that are believed to capture financial constraint, in fact, do not capture financial constraint.

I find that all the effects of credit supply on output price come from the general price effect, rather than arises from the quality and variety change (Table 8). That is, credit-constrained firms do not alter their variety or quality of their products in changing their output price but decrease the existing products' price.

[Table 8 about here.]

3.5.3 Employment Regression

As a robustness check of the measure I am using, I replicate the result in Chodorow-Reich (2014) in my sample. That is, credit-constrained firms lay off the workers (Table 9)

[Table 9 about here.]

3.5.4 Pre-trend

I check the pre-trend of the regression analysis for the robustness check. There is no effect before the Lehman failure as shown in Table 10

[Table 10 about here.]

3.5.5 Different Weight

I used a different regression weight as a robustness and report the result in Table 11. Still, credit-constrained firms decrease their price relative to their counterparts.

[Table 11 about here.]

3.5.6 Retailer Fixed Effects

One concern regarding the regression analysis is a retail-level variation of output price that could potentially correlated with the credit supply shock measure. To address this concern, I allow retailer dimension in the regression with retailer fixed effects. Still, credit-constrained firms decrease their price relative to their counterparts (Table 12).

[Table 12 about here.]

3.5.7 State Fixed Effects

One concern regarding the regression analysis is a local variation of output price that is potentially correlated with the credit supply shock measure. To address this concern, I allow state/regional dimension in the regression with state fixed effects. Still, credit-constrained firms decrease their price relative to their counterparts (Table 13).

[Table 13 about here.]

3.5.8 External Validity

One concern that might arise in this study is the fact that I am only relying on one time period, Lehman failure. To address this, I conduct the similar analysis using different shock and data. I use the following specification:

$$\Delta \ln P_{jt} = \lambda_j + \lambda_t + \delta(\mathrm{RZ}_j \times \Delta f f_t) + \theta X_{jt} + \varepsilon_{jt} \tag{3.12}$$

where j is naics 4-digit industry code, t is month. I gathered BLS monthly industry-level price data for the dependent variable. I build up a Rajan and Zingales (1998) external financial dependence index (RZ_j) from the Compustat database and use a change in exogenous fed fund rate ($\Delta f f_t$) from Romer and Romer (2004) to run this regression. The time period covers from December 1984 to December 1996. X_{jt} is industry-level controls: (NAICS 2-digit)$\times\Delta f f_t$; (Durability)$\times\Delta f f_t$; (Luxuriousness Index)$\times\Delta f f_t$; $\mathrm{RZ}_j\times$(Seasonal Dummies)$_t$. Luxuriousness Index and Durability are come from Bils et al. (2013)

Based on equation (3.12), I find that external finance dependent industries reduce their output price due to the exogenous increase in fed fund rate relative to their counterparts (Table 14). This analysis confirms the empirical studies in previous sections.

[Table 14 about here.]

4 Theoretical Analyses

In this section, I present a business cycle model with credit constrained producers to formalize the mechanism proposed in the last section and discuss the aggregate implications. I first present a simple model to illustrate two channels on how credit supply shock affects output price: "fire-sale" of inventory and "pass-through" of credit cost. Former channel dominates the latter under the standard calibration, leading output price to fall due to a negative credit supply shock. I then extend the model to discuss the dynamics of aggregate inflation, inventory, and other variables. The model is particularly related with Iacoviello (2005) and Wen (2011).

4.1 Simple Model

There are three types of agents in this model: Households and two same groups of entrepreneurs otherwise facing a different degree of credit supply shock. Two identical entrepreneurs are allowed to reflect micro-level analysis expressly. There are two important characteristics of entrepreneurs. First, entrepreneurs face the borrowing capability that is exogenously given to them. I will exogenously decrease one group of entrepreneurs' borrowing capacity to see how their output price dynamics evolve compared to the other. Second, entrepreneurs hold inventory to avoid stock-out arises from product-level idiosyncratic demand shock.

4.1.1 Households

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, l_t^H are hours of work they 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 back $-R_{t-1}b_{t-1}^H$, where R_{t-1} is the interest rate on loans between $t-1$ and t. The 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 household, and c_{2t}^H is produced by entrepreneur 2 and consumed by household. The corresponding price index is given by:

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

where p_{1t} is a price of good 1 and p_{1t} is a price of good 2. Aggregate price index is normalized to one. Solving the above household problem yields the following first-order conditions for the aggregate consumption (4.2), labor supply (4.3), and consumption for good 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 types of entrepreneurs. They are identical otherwise one experiences 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 aggregation consumption of type j entrepreneurs at time t. γ is the discount factor for entrepreneur. I assume entrepreneurs are impatient compared to households ($\gamma < \beta$) as in previous literature. This assumption makes entrepreneurs to borrow from household. Similar to households, entrepreneurs' aggregate consumption index is the following nest of good 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 of 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 hours of work they employ, b_{jt}^{Ej} is borrowing from households, and y_{jt} is a 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 process for type 1 entrepreneurs, but stays constant for type 2 entrepreneurs. Note that equation (4.7) binds at the steady state because entrepreneurs' discount factor is smaller than households'. I further assume shocks are small enough so that this equation always bind.

Type j entrepreneurs produce the good j from the following process. First, they produce multiple intermediate goods ($x_{jt}(i)$) 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. Each produced intermediate goods can be stored in inventory before they are 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 what's left after producer store their intermediate goods ($x_{jt}(i)$) in inventory ($\text{inven}_{jt}(i)$). 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 demand shock to intermediate good ($y_{jt}(i)$). I assume there is an information lag. That is, $\theta(i)$ realizes after entrepreneurs produces the intermediate good $x_{jt}(i)$. In this way, entrepreneurs have the incentive to store goods in inventory in this model. I further assume $\theta(i)$ is drawn from the Pareto distribution for the analytical tractability.

Solution

I solve the above problem with two-stage budgeting problem. First, choose mix of varieties to minimize costs (minimizing $p_{1t}c_{1t}^{Ej} + p_{2t}c_{2t}^{Ej}$ subject to $c_t^{Ej} = \big[(c_{1t}^{Ej})^{\frac{\eta-1}{\eta}} + (c_{2t}^{Ej})^{\frac{\eta-1}{\eta}}\big]^{\frac{\eta}{\eta-1}}$), I get

$$c_{1t}^{Ej} = (\frac{p_{1t}}{p_t})^{-\eta} c_t^{Ej}, j = 1, 2 \tag{4.11}$$

$$c_{2t}^{Ej} = (\frac{p_{2t}}{p_t})^{-\eta} c_t^{Ej}, j = 1, 2 \tag{4.12}$$

At the equilibrium, $c_{jt}^H + c_{jt}^{E1} + c_{jt}^{E2} = y_{jt}$ for j=1,2 and $c_t^H + c_t^{E1} + c_t^{E2} = y_t$. (goods market clearing for good 1 and 2 and for the aggregate good). Adding up the above demand equations with household demand for each good and by using a goods market clearing condition, we get $y_{jt} = (p_{jt})^{-\eta} y_t$ or

$$p_{jt} = (\frac{y_{jt}}{y_t})^{-\frac{1}{\eta}}, \quad j = 1, 2 \tag{4.13}$$

Thus, one can rewrite equation (4.6) by substituting p_{jt}:

$$c_t^{Ej} + w_t l_t^{Ej} + R_{t-1} b_{t-1}^{Ej} = b_t^{Ej} + y_{jt}^{\frac{\eta-1}{\eta}} y_t^{\frac{1}{\eta}}, \;\; y_{jt} \equiv \Big[\int_0^1 \theta(i)(y_{jt}(i))^{\rho} di\Big]^{\frac{1}{\rho}} \tag{4.14}$$

Second, denoting $x_{jt} \equiv \int_0^1 x_{jt}(i)di$, $s_t \equiv \text{inven}_t$ 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)-(4.9) and (4.14), respectively. For simplicity, suppress notation for entrepreneurs (Ej, their solutions are identical). First order conditions for $\{c_t, l_t, s_{jt}(i), y_{jt}(i), x_{jt}(i), b_t\}$ are:

$$\frac{1}{c_t^{\sigma_c}} = \lambda_{1,t} \tag{4.15}$$

$$\lambda_{1,t} - \eta_t - \gamma E_t \lambda_{1,t+1} R_t = 0 \tag{4.16}$$

$$\lambda_{1,t} w_t = \lambda_{3,t}(1-\alpha)\frac{x_t}{l_t} \tag{4.17}$$

$$\lambda_{1,t}\frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}} \theta_t(i) y_t(i)^{\rho-1} = \lambda_{2,t}(i) \tag{4.18}$$

$$\lambda_{3,t} = E_t^i \lambda_{2,t}(i) = \int \lambda_{2,t}(i) dF(\theta_t) \tag{4.19}$$

$$\lambda_{2,t}(i) = \gamma E_t\big[\lambda_{2,t+1}(i)\big] + \xi_t(i) \tag{4.20}$$

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 (4.19) shows the information lag with E^i.

Decision Rules for Inventories

I follow Wen (2011) carefully to solve this problem. The key to solve 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:

$$\lambda_{2,t}(i) = \gamma E_t \lambda_{3,t+1} + \xi_t(i) \tag{4.21}$$

Two possible cases to consider:

- CASE A: Suppose $\theta(i) \leq \theta^*$. We then have $\xi(i) = 0, s(i) \geq 0$, and $\lambda_{2,t}(i) = \gamma E_t \lambda_{3,t+1}$. The budget constraint (4.9) implies that $y_{jt}(i) \leq x_{jt}(i) + s_{j,t-1}(i)$. Since equation (4.18) 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 $\theta(i) \leq \left[x_{jt}(i)+s_{j,t-1}(i)\right]^{1-\rho}\left[\frac{\gamma E_t \lambda_{3,t+1}}{\lambda_{1,t}\frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}}}\right] \equiv \theta^*$, 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 (4.18) 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 (4.21) can be written as

$$\lambda_{3,t} = \int_{\theta(i) \leq \theta^*} (\gamma E_t \lambda_{3,t+1}) dF(\theta) + \int_{\theta(i) > \theta^*} (\gamma E_t \lambda_{3,t+1}) \frac{\theta_t(i)}{\theta^*} dF(\theta) \tag{4.22}$$

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 stockout. Thus, the optimal cutoff value is determined at the point where the marginal cost equals the expected marginal benefit. Since aggregate variables are independent of idiosyncratic shocks, the equation (4.22) can be written as

$$\lambda_{3,t} = \gamma E_t \lambda_{3,t+1} R^I(\theta_t^*) \tag{4.23}$$

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 $\frac{dR^I(\theta^*)}{d\theta^*} < 0$.

Given aggregate economic condition, the equation (4.23) 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:

$$x_{jt}(i) + s_{j,t-1}(i) = \left[\frac{\lambda_{1,t} \frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}} \theta^*}{\gamma E_t \lambda_{3,t+1}} \right]^{\frac{1}{1-\rho}} \tag{4.24}$$

$$y_{jt}(i) = \left[\frac{\lambda_{1,t} \frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}}}{\gamma E_t \lambda_{3,t+1}} \right]^{\frac{1}{1-\rho}} \times \min \left\{ \theta_t(i)^{\frac{1}{1-\rho}}, \theta_t^{*\frac{1}{1-\rho}} \right\} \tag{4.25}$$

$$s_t(i) = \left[\frac{\lambda_{1,t} \frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}}}{\gamma E_t \lambda_{3,t+1}} \right]^{\frac{1}{1-\rho}} \times \max \left\{ \theta_t^{*\frac{1}{1-\rho}} - \theta_t(i)^{\frac{1}{1-\rho}}, 0 \right\} \tag{4.26}$$

The shadow price of inventory i is determined by

$$\lambda_{2,t}(i) = \gamma E_t \lambda_{3,t+1} \times \max \left\{ 1, \frac{\theta(i)}{\theta^*} \right\} \tag{4.27}$$

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 (4.24)-(4.26) under the law of large numbers gives

$$Y_{jt} = \left[\frac{\lambda_{1,t} \frac{\eta-1}{\eta} y_{jt}^{\frac{\eta-1-\rho\eta}{\eta}} y_t^{\frac{1}{\eta}}}{\gamma E_t \lambda_{3,t+1}} \right]^{\frac{1}{1-\rho}} D(\theta_t^*) \tag{4.28}$$

$$x_{jt} + s_{j,t-1} = Y_{jt} \frac{D(\theta_t^*) + H(\theta_t^*)}{D(\theta_t^*)} \tag{4.29}$$

$$s_{jt} = Y_{jt} \frac{H(\theta_t^*)}{D(\theta_t^*)} \tag{4.30}$$

and aggregating the first-order condition (14) gives

$$\lambda_{3,t} = \lambda_{1,t} R^I(\theta_t^*) G(\theta^*)^{\frac{1-\rho}{\rho}} \left\{ \frac{\eta-1}{\eta} \left(\frac{y_t}{y_{jt}} \right)^{\frac{1}{\eta}} \right\} \tag{4.31}$$

where

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

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

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

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

Entrepreneur-level Optimality Conditions

First order conditions with aggregate variables:

$$
\frac{1}{c_t^{\sigma_c}} = E_t\frac{\gamma R_t}{c_{t+1}^{\sigma_c}} + \eta_t \tag{4.32}
$$

$$
w_t = (1-\alpha)\frac{x_{jt}R^I(\theta_{jt}^*)G(\theta_{jt}^*)^{\frac{1-\rho}{\rho}}}{l_t}\left\{\frac{\eta-1}{\eta}\left(\frac{y_t}{y_{jt}}\right)^{\frac{1}{\eta}}\right\} \tag{4.33}
$$

$$
\frac{G(\theta_{jt}^*)^{\frac{1-\rho}{\rho}}\left(\frac{y_t}{y_{jt}}\right)^{\frac{1}{\eta}}}{c_t^{\sigma_c}} = \gamma E_t\left\{\frac{R^I(\theta_{j,t+1}^*)G(\theta_{j,t+1}^*)^{\frac{1-\rho}{\rho}}\left(\frac{y_{t+1}}{y_{jt+1}}\right)^{\frac{1}{\eta}}}{c_{t+1}^{\sigma_c}}\right\} \tag{4.34}
$$

Corresponds to the Euler equation, labor demand, and inventory demand.

The aggregate budget constraints are:

$$
c_t + w_t l_t + R_{t-1}b_{t-1} - b_t = p_{jt}\frac{y_{jt}}{Y_{jt}}\left[a_t(l_t)^{1-\alpha} + s_{j,t-1} - s_{jt}\right] \tag{4.35}
$$

$$
s_{jt} = Y_{jt}\frac{H(\theta_{jt}^*)}{D(\theta_{jt}^*)} \tag{4.36}
$$

$$
x_{jt} + s_{j,t-1} = Y_{jt}\frac{D(\theta_{jt}^*) + H(\theta_{jt}^*)}{D(\theta_{jt}^*)} \tag{4.37}
$$

$$b_t = \bar{b}_t \tag{4.38}$$

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.

4.1.3 Discussion, Calibration, and Result

There are two channels on how adverse credit supply shock affects output price dynamics: "fire-sale" of inventory and "pass-through" of credit cost. Consider a case without inventory to see how "pass-thorough" channel works. When entrepreneurs experience an exogenous decrease in their borrowing, they cut their consumption and labor demand based on their budget constraint. Since they reduce their input (labor), this leads to a decline in their production and increase in output price as products are a substitute. However, with the presence of inventory, credit-constrained entrepreneurs can generate additional revenue by selling off their inventory. The decrease in consumption and labor demand are smaller compared to the case without inventory at the time of the credit crunch.

The strength of two forces is governed by one parameter, α, in this model. The α is a production function parameter that drives the "pass-through" channel. If α is small, a decrease in labor demand due to credit constraint have a large effect on the production of goods, hence result in an increase in output price. I show that under the standard calibration of $\alpha = 0.33$, the "fire-sale" effect dominates and leads to decrease in output price due to the adverse credit supply shock. However, if I make α artificially small, the "pass-through" effect dominates and output price increase as a consequence of the adverse credit supply shock.

Calibration of other parameters is very standard as in Table 15. 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 $\ln(\bar{b}_t) = \rho^{\bar{b}} \ln(\bar{b}_{t-1}) + \epsilon_t^{\bar{b}}$. Calibration of inventory parameters (ξ and η) follows Wen (2011).

[Table 15 about here.]

In this simple model, I discuss the differential dynamics of variables to illustrate the micro-level empirical analysis. A thought experience here is the exogenous decrease in type 1 entrepreneurs' borrowing capabilities. The figure 3 shows the result with the different value of the production function parameter α.

[Figure 3 about here.]

There is a decrease in relative output price, inventory, employment, and an increase in relative market share (or output) due to the negative credit supply shock under the standard calibration. These results are consistent with the micro-level analysis.

4.2 Extended Model

I extend the simple model by adding retailers with Calvo-Yun price rigidity, Central Bank that follows a Taylor Rule, credit-constrained impatient households, capital investment, and housing market to address the aggregate inflation dynamics. I added price rigidity and Central Bank to discuss the *aggregate* inflation dynamics. Adding impatient households, real estate market, and capital investment help to think about the more realistic effect of the adverse credit supply shock and its interaction with other important features of the business cycle fluctuation. One can think of this model as an extension of the model in Iacoviello (2005), allowing two identical entrepreneurs with a stockout avoidance motive of inventory holding as in Wen (2011).

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

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

where $p_{jt}(z)$ is the "reset" price and $y_{j,t+s}(z)$ 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.

Central bank follows a following Taylor Rule:

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

where R_t is interest rate at time t and y_t^{GDP} is the total production in the economy at time t. I made a Central Bank to respond the previous economic condition to isolate the effect of monetary policy from a credit supply shock, consistent with Iacoviello (2005).

Impatient households discount the future more heavily than the patient counterparts and face the collateral constraint. Otherwise, they are identical to patient households. They maximize a lifetime utility function given by

$$E_0 \sum_{t=0}^{\infty} (\beta^{Hi})^t \left[\frac{(c_t^{Hi})^{1-\sigma_c}}{1-\sigma_c} + \frac{(h_{1t}^{Hi})^{1-\sigma_h}}{1-\sigma_h} + \frac{(h_{2t}^{Hi})^{1-\sigma_h}}{1-\sigma_h} - \frac{(l_t^{Hi})^{1+\sigma_l}}{1+\sigma_l} + \chi \frac{(M_t^{Hi}/p_t)^{1-\sigma_m}}{1+\sigma_m} \right]$$

where is the housing used by type 1 entrepreneurs consumed by impatient households at time t, l^{Hi} is the labor they supply, and M_t^{Hi}/p_t is the real money holding. Housing and money holdings in utility are also reflected in the patient households problem. Assuming the small discount factor, $\beta^{Hi} < \beta$, guarantees an equilibrium in which impatient households face the binding borrowing constraint. The flow of funds and the collateral constraints (borrowing limits) are:

$$c_t^{Hi} + q_{1t}\Delta h_{1t}^{Hi} + \xi_{1t} + q_{2t}\Delta h_{2t}^{Hi} + \xi_{2t} + R_{t-1} b_{t-1}^{Hi}/\pi_t = b_t^{Hi} + w_t l_t^{Hi} + T_t^{Hi} - \Delta M_t^{Hi}/p_t \quad (4.39)$$

where $\xi_{jt} = \frac{\psi_h}{2}\left(\frac{h_{jt}^{Hi}}{h_{j,t-1}^{Hi}} - 1\right)^2 q_{jt} h_{j,t-1}^{Hi}$ is the adjustment cost of type j housing. The borrowing or collateral constraint is:

$$b_t^{Hi} \leq m^{Hi} E_t \left[(q_{1,t+1} h_{1t}^{Hi} + q_{2,t+1} h_{2t}^{Hi}) \pi_{t+1}/R_t \right] \quad (4.40)$$

where m^{Hi} is the loan-to-value ratio and the similar collater constraint is in the entrepreneur's problem. The borrowing constraint is consistent with standard lending criteria used in the mortgage market, which limit the amount lent to a fraction of the value of the asset. One can interpret the case $m_t^{Hi} = 0$ as the limit situation when housing is not collateralizable at all so that households are excluded from financial markets.

I added this collateral constraint condition also in the entrepreneur's problem. Type j entrepreneurs face the following collateral constraints

$$b_t^{Ej} \leq m_t^{Ej} E_t(q_{j,t+1} h_{jt} \pi_{t+1}/R_t) \text{ (binds due to impatience)}$$

where the m_t^{Ej} is the loan-to-value ratio for type j entrepreneurs that follow an exogenous process as in Liu et al. (2013). Allowing time-varying loan-to-value ratio generates an exogenous credit supply shock in this model.[13].

Based on this environment, I find that drop in one group of entrepreneurs' loan-to-value ratio leads to drop in *aggregate* inflation and GDP, and at the same time captures relative decrease in output price and production (Figure 4).

[Figure 4 about here.]

5 Conclusion

In this paper, I find that credit-constrained firms decrease their output price based on the novel micro-level data and a change in bank health at the time of Lehman failure as an exogenous variation on companies' credit condition. I posit a "fire-sale" of inventory hypothesis to explain this empirical finding: credit-constrained firms decrease their price since they are quickly selling off their inventories and dump their products in low price to generate extra cash flow. I empirically support this hypothesis by first showing that both aggregate inflation and inventory fall in the data, and that credit-constrained firms drop their inventory temporarily and increase their market share. I then build up a simple dynamics general equilibrium model to formalize and illustrate this mechanism explicitly. The model features two mechanisms, the "fire-sale" of inventory channel emphasized in this paper and the "pass-through" of credit cost channel discussed in the previous studies. Due to the adverse credit supply shock, the model predicts a drop in the relative price of credit-constrained firms consistent with the micro-level evidence, but a rise in relative price without incorporating inventory.

This paper suggests that a credit-constrained is an important determinant of output price dynamics, especially during the Great Recession. In particular, inventory, which has not been addressed in explaining output price dynamics, is crucial to address output price dynamics. Models that features these ingredients would better account for the fluctuation of inflation, inventory, and other aggregate variables.

[13] As discussed in Gerali et al. (2010) and Bachmann and Ruth (2016), this is a parsimonious way to allow a credit supply shock in the business cycle model

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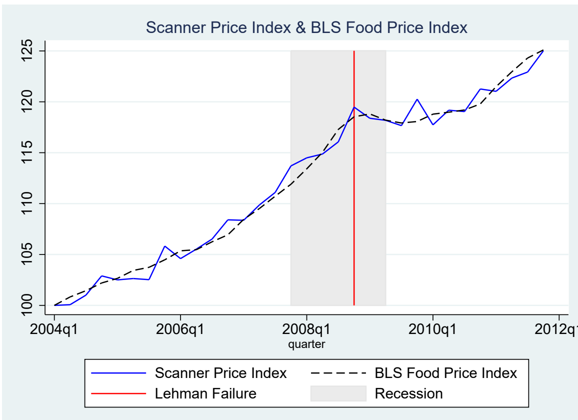
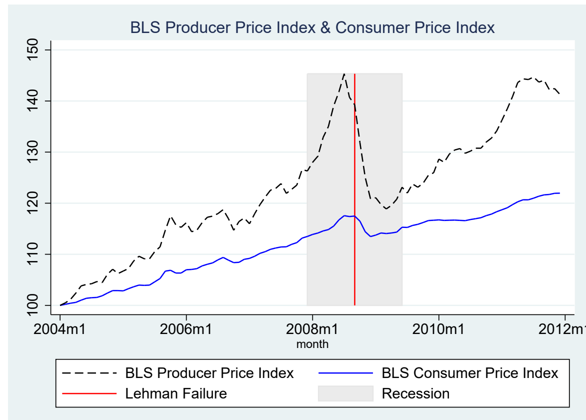
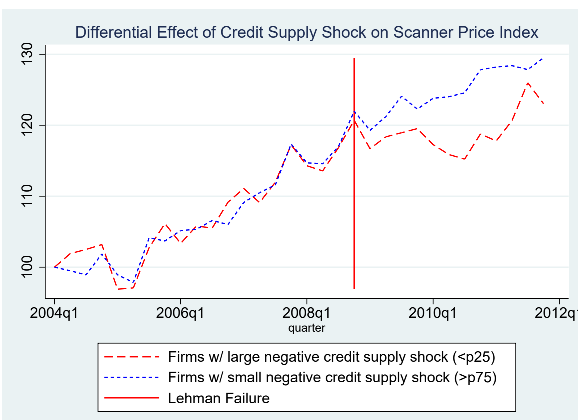
Figure 1: Inflation and Inventory Dynamics after the Lehman failure



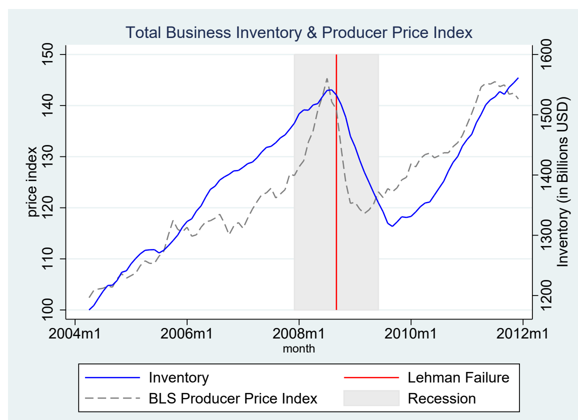
(a) Scanner and BLS food price Index



(b) BLS CPI and PPI



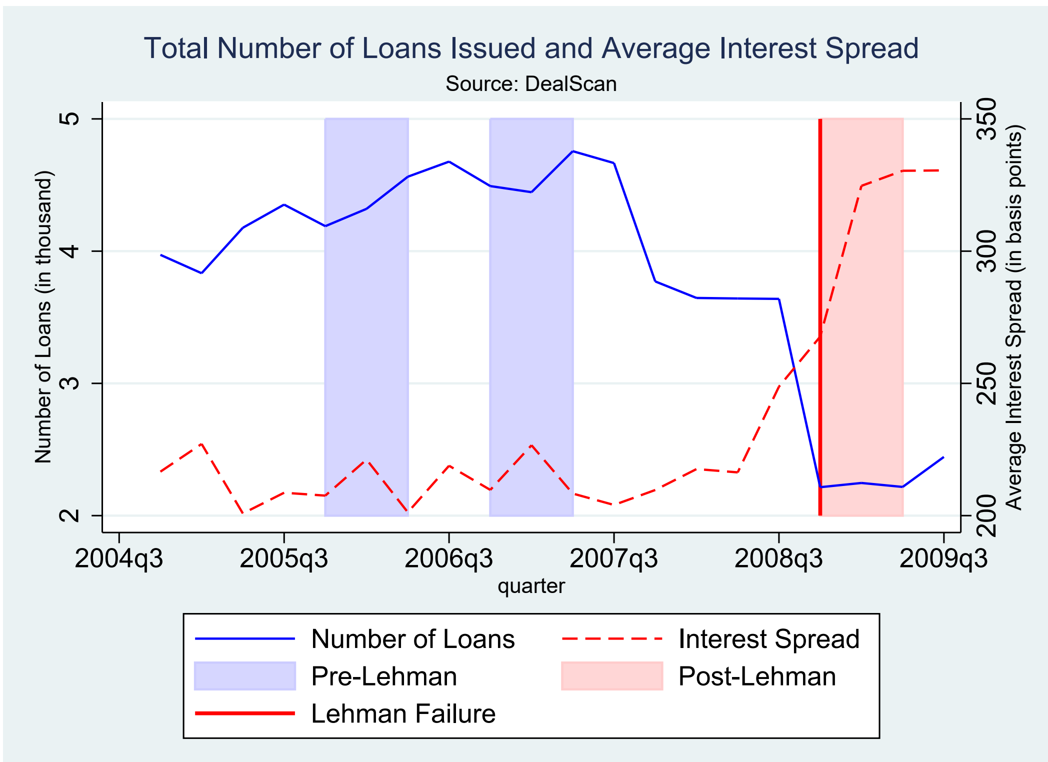
(c) Differential change in scanner price index



(d) Inventory dynamics

Note. (a) plots the scanner price index, which is constructed from the ACNielsen Homescan Panel data, along with the BLS food price index. (b) shows the BLS consumer price index and producer price index. (c) shows differential change in price index between credit-constrained firms and their unaffected counterparts. (d) shows the aggregate inventory dynamics

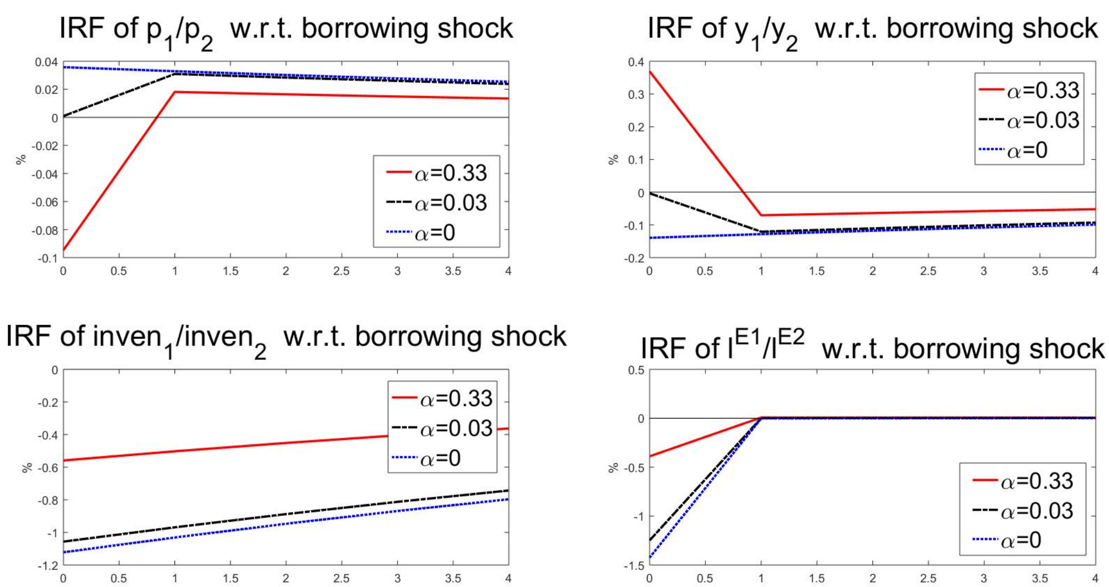
Figure 2: Timing for the Credit Supply Shock (ΔL_f)



Note. Pre-Lehman period is the following 6 quarters: 2005Q4-2006Q2 and 2006Q4-2007Q2. Post-Lehman period is the following 3 quarters: 2008Q4-2009Q2. Number of loans are total number of loans issued in the Dealscan database and interest spread is the amount borrower pays in basis points over LIBOR for each dollar drawn down. Lehman Failure happened on September 2008, at the end of 2008Q3.

Figure 3: Differential Response of Price, Output, Inventory, and Employment

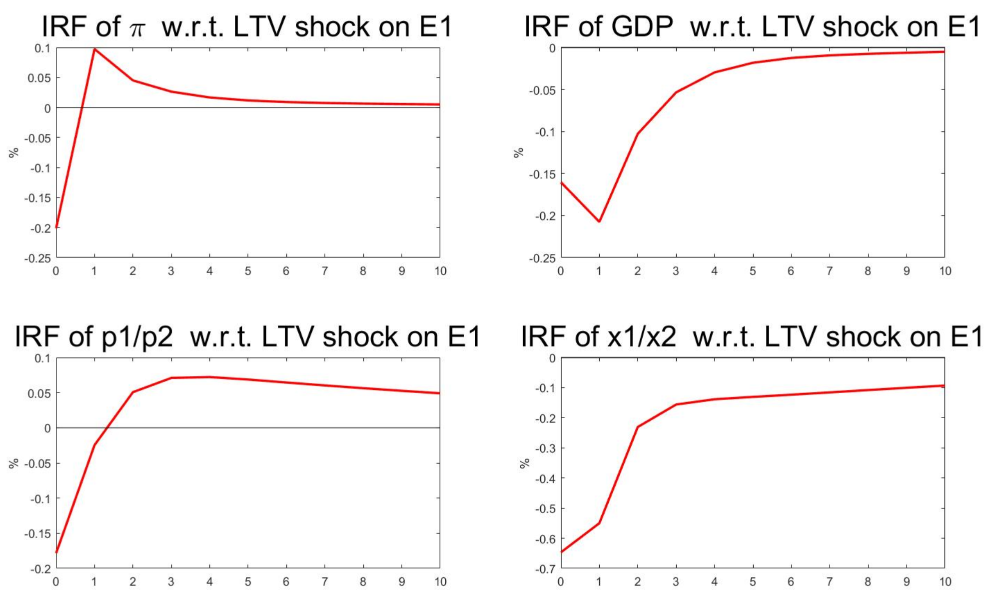
with respect to the Negative Credit Supply Shock



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

Figure 4: Aggregate and Differential Response of Price and Production

with respect to the Negative Credit Supply Shock



Note. Top-left shows the dynamics of aggregate inflation, top-right shows the dynamics of aggregate GDP, bottom-left shows the dynamics of relative output price, and bottom-right shows the dynamics of relative production due to the negative credit supply shock to type 1 entrepreneurs.

Table 1: The Effect of Credit Crunch on Output Price

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\ln\mathrm{P}_{\mathrm{fg}}$: 2006q4-2007q2 to 2008q4-2009q2					
	OLS		ΔL_{f} instrumented using			
			Lehman	ABX	BankItem	All
ΔL_{f}	-0.049***	-0.182***	-0.169**	-0.147**	-0.178***	-0.168***
	(0.016)	(0.033)	(0.077)	(0.066)	(0.066)	(0.049)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
product group FE	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			17.30	9.00	13.20	10.80
J-statstics p-value						0.92
$E[\Delta\ln\mathrm{P}]$	.114	.114	.114	.114	.114	.114
$E[\Delta\ln\mathrm{P}{:}\Delta L_{\mathrm{p90}}\text{-}\Delta L_{\mathrm{p10}}]$	-.049	-.184	-.171	-.148	-.179	-.169
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; regression is 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, lagged $\Delta\ln\mathrm{P}_{\mathrm{fg}}$. A sign of the credit supply measure (ΔL_f) is changed to capture the adverse effect on output price.

Table 2: The Effect of Credit Crunch on Inventory

	(1)	(2)	(3)	(4)	(5)	(6)
	Inventory Growth (g_f^{Inv}): **2006 to 2008**					
	OLS		ΔL_{f} instrumented using			
			Lehman	ABX	BankItem	All
ΔL_{f}	-0.142***	-0.151***	-0.398***	-0.694***	-0.722***	-0.550***
	(0.053)	(0.043)	(0.137)	(0.165)	(0.188)	(0.124)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			61.00	27.60	18.00	13.60
J-statstics p-value						0.16
$E[g^{\text{Inv}}]$	.013	.013	.013	.013	.013	.013
$E[g^{\text{Inv}} : \Delta L_{\text{p90}}\text{-}\Delta L_{\text{p10}}]$	-.179	-.19	-.5	-.872	-.907	-.691
Observations	958	958	958	958	958	958
	(7)	(8)	(9)	(10)	(11)	(12)
	Inventory Growth (g_f^{Inv}): **2008 to 2010**					
	OLS		ΔL_{f} instrumented using			
			Lehman	ABX	BankItem	All
ΔL_{f}	0.044	0.065*	0.460**	0.303*	0.231	0.335**
	(0.045)	(0.034)	(0.205)	(0.165)	(0.199)	(0.162)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			37.10	22.30	21.10	13.00
J-statstics p-value						0.35
$E[g^{\text{Inv}}]$	.036	.036	.036	.036	.036	.036
$E[g^{\text{Inv}} : \Delta L_{\text{p90}}\text{-}\Delta L_{\text{p10}}]$	.055	.081	.577	.381	.291	.421
Observations	898	898	898	898	898	898

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by naics3; weighted by initial inventory; Firm-level controls are: listed, 2-digit NAICS FE, number of loans, multi-lead FE, spread, number of loans due in post-Lehman FE, size indicator, bond rating. A sign of the credit supply measure (ΔL_f) is changed to capture the adverse effect on output price.

Table 3: The Effect of Credit Crunch on Market Share

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔS_{fg}: 2006q4-2007q2 to 2008q4-2009q2					
	OLS		ΔL_f instrumented using			
			Lehman	ABX	BankItem	All
ΔL_f	-0.008	0.020**	0.052**	0.009	0.044**	0.041**
	(0.008)	(0.010)	(0.026)	(0.017)	(0.018)	(0.018)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
product group FE	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			18.90	7.60	16.50	12.20
J-statstics p-value						0.17
$E[\Delta S]$	-.004	-.004	-.004	-.004	-.004	-.004
$E[\Delta S{:}\Delta L_{p90}\text{-}\Delta L_{p10}]$	-.008	.02	.053	.009	.045	.041
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: 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

Table 4: The Effect of Firms' Cash Holding on Output Price

	(1)	(2)	(3)	(4)
	$\Delta \ln P_{fg}$: 2006q4-2007q2 to 2008q4-2009q2			
	LIQ_f is $-\Delta \frac{\text{cash}}{\text{total asset}}$		LIQ_f is $-(\frac{\text{cash}}{\text{total asset}})_{2006}$	
LIQ_f	-0.027	0.022***	0.091***	0.063**
	(0.040)	(0.000)	(0.024)	(0.025)
firm-level controls	No	Yes	No	Yes
product group FE	No	Yes	No	Yes
$E[\Delta \ln P]$	.095	.095	.095	.095
$E[\Delta \ln P{:}\Delta L_{p90}\text{-}\Delta L_{p10}]$	-.014	.011	.074	.051
Observations	1316	1171	1524	1376

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by firm and product group; Firm-level controls are: 4-digit NAICS FE, age, bond rating, multi-lead FE, spread

Table 5: The Effect of Credit Crunch on Firms' Cash Holding

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\frac{\text{cash}}{\text{total asset}}$: 2006 to 2008					
	OLS		ΔL_{f} instrumented using			
			Lehman	ABX	BankItem	All
ΔL_{f}	0.073*	0.068**	0.365**	0.101	0.350***	0.258**
	(0.040)	(0.033)	(0.157)	(0.152)	(0.113)	(0.112)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			21.60	22.20	40.10	19.90
J-statstics p-value						0.21
$E[\Delta \ln \text{Inv}]$	.062	.062	.062	.062	.062	.062
$E[\Delta \ln \text{Inv}{:}\Delta L_{\text{p90}}\text{-}\Delta L_{\text{p10}}]$	.093	.086	.463	.128	.443	.327
Observations	1213	1213	1213	1213	1213	1213

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by 3-digit NAICS; Firm-level controls: initial employment, spread, number of loans due in post-Lehman, sector FE

Table 6: The Effect of Credit Crunch on Output Price: Including Initial Cash Holding

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \ln P_{fgs}$: 2006q4-2007q2 to 2008q4-2009q2					
	OLS		IV (ΔL_f)	OLS		IV (ΔL_f)
			All			All
ΔL_{f}	-0.047***	-0.095***	-0.122**	-0.046***	-0.086***	-0.120**
	(0.018)	(0.032)	(0.051)	(0.017)	(0.026)	(0.048)
$\overline{(\frac{\text{cash}}{\text{total asset}})}_{2006\text{to}07}$	-0.010	0.080	0.095			
	(0.029)	(0.093)	(0.106)			
$(\frac{\text{cash}}{\text{total asset}})_{2006}$				-0.022*	0.054	0.055
				(0.011)	(0.063)	(0.069)
firm-level controls	No	Yes	Yes	No	Yes	Yes
product group FE	No	Yes	Yes	No	Yes	Yes
First-stage F statistics			5.00			6.10
J-statstics p-value			0.27			0.12
$E[\Delta \ln P]$	.115	.115	.115	.115	.115	.115
$E[\Delta \ln P{:}\Delta L_{p90}\text{-}\Delta L_{p10}]$	-.048	-.096	-.123	-.047	-.087	-.121
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; 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 $\Delta \ln P_{fg}$

Table 7: The Differential Effect of Credit Crunch on Output Price with Initial Cash Holding

	$\Delta \ln \mathrm{P}_{fg}$
$\mathrm{D}_{f,(\mathrm{cash}_{t_0}<\mathrm{cash}_{t_0,p50})} \times \Delta \mathrm{L}_f$	-0.329**
	(0.140)
$\mathrm{D}_{f,(\mathrm{cash}_{t_0}<\mathrm{cash}_{t_0,p50})}$	0.047
	(0.047)
ΔL_{f}	-0.146*
	(0.077)
firm-level controls	Yes
product group FE	Yes
Observations	774

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by 3-digit NAICS; Firm-level controls: initial employment, initial revenue, number of loans, amount of loans, initial cash/total asset, initial inventory and its interaction with $\Delta \mathrm{L}_f$

Table 8: The Effect of Credit Crunch on Output Price: Decomposition

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\ln\tilde{P}_{\mathrm{fg}}$: 2006q4-2007q2 to 2008q4-2009q2					
	OLS		ΔL_{f} instrumented using			
			Lehman	ABX	BankItem	All
ΔL_{f}	-0.050***	-0.178***	-0.170*	-0.159**	-0.150*	-0.158***
	(0.011)	(0.041)	(0.089)	(0.071)	(0.078)	(0.052)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
product group FE	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			17.20	9.10	13.30	10.80
J-statstics p-value						0.98
$E[\Delta\ln\mathrm{P}]$	.114	.114	.114	.114	.114	.114
$E[\Delta\ln\mathrm{P}{:}\Delta L_{\mathrm{p90}}\text{-}\Delta L_{\mathrm{p10}}]$	-.05	-.18	-.171	-.16	-.152	-.159
Observations	1658	1658	1658	1658	1658	1658
	(7)	(8)	(9)	(10)	(11)	(12)
	$\Delta\ln SD_{\mathrm{fg}}$: 2006q4-2007q2 to 2008q4-2009q2					
	OLS		ΔL_{f} instrumented using			
			Lehman	ABX	BankItem	All
ΔL_{f}	0.001	-0.000	0.010	0.010	-0.021	-0.004
	(0.007)	(0.017)	(0.030)	(0.022)	(0.025)	(0.016)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
product group FE	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			16.90	9.20	13.10	10.90
J-statstics p-value						0.54
$E[\Delta\ln\mathrm{P}]$	0	0	0	0	0	0
$E[\Delta\ln\mathrm{P}{:}\Delta L_{\mathrm{p90}}\text{-}\Delta L_{\mathrm{p10}}]$	.001	0	.01	.01	-.021	-.004
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: 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 9: The Effect of Credit Crunch on Employment

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment Growth (Δg_f^E): 2006 to 2008					
	OLS		ΔL_{f} instrumented using			
			Lehman	ABX	BankItem	All
ΔL_{f}	-0.134***	-0.124***	-0.288**	-0.524***	-0.389**	-0.392**
	(0.039)	(0.042)	(0.139)	(0.142)	(0.194)	(0.157)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			66.70	34.10	83.10	38.20
J-statstics p-value						0.15
$E[\Delta g^E]$	-.005	-.005	-.005	-.005	-.005	-.005
$E[\Delta g^E : \Delta L_{\mathrm{p90}}\text{-}\Delta L_{\mathrm{p10}}]$	-.167	-.154	-.36	-.653	-.486	-.489
Observations	1011	1011	1011	1011	1011	1011

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by 3-digit NAICS; weighted by initial employment; Firm-level controls: listed, 1-digit NAICS FE, number of loans, amount of loans, 2005 revenue, number of lead, spread, maturity, multi-lead FE

Table 10: The Effect of Credit Crunch on Output Price: Pre-Trend

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \ln P_{fg}$: 2004q4-2005q2 to 2006q4-2007q2					
	OLS		ΔL_f instrumented using			
			Lehman	ABX	BankItem	All
ΔL_f	-0.017	-0.076	0.040	-0.140	-0.145	-0.090
	(0.026)	(0.063)	(0.098)	(0.103)	(0.112)	(0.078)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
product group FE	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			16.80	9.20	13.40	10.80
J-statstics p-value						0.21
$E[\Delta \ln P]$	.049	.049	.049	.049	.049	.049
$E[\Delta \ln P{:}\Delta L_{p90}\text{-}\Delta L_{p10}]$	-.017	-.077	.04	-.142	-.147	-.091
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 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

Table 11: The Effect of Credit Crunch on Output Price: Different Weight

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \ln \mathrm{P}_{\mathrm{fg}}$: 2006q4-2007q2 to 2008q4-2009q2					
weight	Sales		Number of UPC		None	
ΔL_f	-0.049***	-0.182***	-0.048***	-0.121***	-0.061***	-0.018
	(0.016)	(0.033)	(0.016)	(0.028)	(0.024)	(0.038)
firm-level controls	No	Yes	No	Yes	No	Yes
product group FE	No	Yes	No	Yes	No	Yes
$E[\Delta \ln \mathrm{P}]$	.114	.114	.114	.114	.114	.114
$E[\Delta \ln \mathrm{P}{:}\Delta L_{\mathrm{p90}}\text{-}\Delta L_{\mathrm{p10}}]$	-.049	-.184	-.049	-.122	-.062	-.018
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: 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 12: The Effect of Credit Crunch on Output Price: Retailer Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\ln\tilde{P}_{\mathrm{fgr}}$: 2006q4-2007q2 to 2008q4-2009q2					
	OLS		ΔL_{f} instrumented using			
			Lehman	ABX	BankItem	All
ΔL_{f}	-0.047***	-0.072***	-0.121***	-0.094**	-0.079*	-0.095***
	(0.011)	(0.017)	(0.031)	(0.037)	(0.044)	(0.032)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
product group FE	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			25.60	16.30	24.50	13.30
J-statstics p-value						0.43
$E[\Delta\ln\mathrm{P}]$	.102	.102	.102	.102	.102	.102
$E[\Delta\ln\mathrm{P}$:ΔL_{p90}-$\Delta L_{\mathrm{p10}}]$	-.047	-.072	-.122	-.095	-.079	-.096
Observations	40519	40519	40519	40519	40519	40519

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 13: The Effect of Credit Crunch on Output Price: State Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\ln\tilde{P}_{\text{fgs}}$: 2006q4-2007q2 to 2008q4-2009q2					
	OLS		ΔL_{f} instrumented using			
			Lehman	ABX	BankItem	All
ΔL_{f}	-0.054***	-0.100***	-0.084**	-0.210***	-0.094*	-0.121***
	(0.012)	(0.022)	(0.043)	(0.079)	(0.054)	(0.042)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
product group FE	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			23.90	13.30	13.30	12.70
J-statstics p-value						0.14
$E[\Delta\text{lnP}]$	.109	.109	.109	.109	.109	.109
$E[\Delta\text{lnP}:\Delta L_{\text{p90}}\text{-}\Delta L_{\text{p10}}]$	-.054	-.101	-.085	-.212	-.094	-.123
Observations	26894	26894	26894	26894	26894	26894

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 14: The Effect of Credit Crunch on Output Price: External Validity

Dependent Variable:		$\Delta \ln P_{jt}$	
	(1)	(2)	(3)
$\text{RZ}_j \times \Delta ff_t$	-0.142**	-0.172**	-0.173**
	(0.072)	(0.082)	(0.083)
$\text{RZ}_j \times \Delta ff_{t-1}$			0.032
			(0.049)
industry & month FE	Yes	Yes	Yes
industry-level controls	Yes	Yes	Yes
seasonal dummies	No	Yes	Yes
Observations	3467	3467	3464
R^2	0.071	0.077	0.077

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by month; Controls are: (NAICS 2-digit)$\times\Delta ff_t$; (Durability)$\times\Delta ff_t$; (Luxuriousness Index)$\times\Delta ff_t$; $\text{RZ}_j\times$(Seasonal Dummies)$_t$

Table 15: Calibration

parameter	meaning/governing	value
β	HH discount factor	0.99
γ	E1 and E2 discount factor	0.98
σ_c	intertemporal elasticity	1
σ_l	frisch elasticity	4
ρ	production elasticity of substitution	0.1
ξ	product-level shock distribution parameter	3
η	demand elasticity of substitution	3.9
$\rho^{\bar{b}}$	borrowing shock parameter	0.95
$\sigma_{\bar{b}}$	borrowing shock parameter	10