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

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CONTENTS

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S1 MODEL

This section presents three different models that relate output prices, inventory, and the credit supply shock. The first model in section S1.A is a general equilibrium model with two identical entrepreneurs with inventory holding to match the differential change in variables in the micro-level data. The second model in section S1.B extends the first model by integrating price rigidity and a central bank to analyze the aggregate inflation dynamics. Figure V is based on this model. The last model in section S1.C is an analytical example of a tractable partial equilibrium model that clarifies the relationship among output price, inventory, and the financial shock (a change in the real interest rate). The first two models are the combination and simplification of Iacoviello (2005) and Wen (2011), whereas the last model is a simple analytical example of the model presented in Alessandria, Kaboski, and Midrigan (2010).

S1.A Simple General Equilibrium Model

There are three types of agents in this model: households and two otherwise identical representative entrepreneurs that face different degrees of credit supply shock. Two identical entrepreneurs are included 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 entrepreneur.

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, which gives companies an incentive to hold both inventory and capital. This feature is useful in the extended model in which entrepreneurs invest in capital.

S1.A.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 the hours of work that households supply for entrepreneurs. Denote $w_t \equiv W_t/P_t$ as 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

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

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

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

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

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

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 (2), labor supply (3), and consumption of goods 1 (4) and 2 (5):

$$\frac{1}{(c_t^H)^{\sigma_c}} = \beta E_t\left[\frac{R_t}{(c_{t+1}^H)^{\sigma_c}}\right] \tag{2}$$

$$w_t = (l_t^H)^{\sigma_l}(c_t^H)^{\sigma_c} \tag{3}$$

$$c_{1t}^H = \left(\frac{p_{1t}}{p_t}\right)^{-\sigma_f} c_t^H \tag{4}$$

$$c_{2t}^H = \left(\frac{p_{2t}}{p_t}\right)^{-\sigma_f} c_t^H \tag{5}$$

S1.A.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 that entrepreneurs are more impatient than households ($\gamma < \beta$). This assumption ensures that entrepreneurs borrow from households. Similar to households, the entrepreneurs' aggregate consumption index is the following nest of goods 1 and 2

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

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

$$c_t^{Ej} + w_t l_t^{Ej} + R_{t-1} b_{t-1}^{Ej} = b_t^{Ej} + p_{jt} y_{jt} \tag{6}$$

where l_{jt}^{Ej} is the hours of work that entrepreneurs 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:

$$b_t^{Ej} \leq \bar{b}_t^{Ej} \tag{7}$$

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 (7) binds at the steady state because the entrepreneurs' discount factor is smaller than the discount factor of households. I further assume that shocks are small enough that this equation always binds.

Type j entrepreneurs produce good j by 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.

$$\int_0^1 x_{jt}(i)di \leq (l_t^{Ej})^{1-\alpha} \tag{8}$$

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

$$\begin{aligned} y_{jt}(i) + \text{inven}_{jt}(i) &\leq \text{inven}_{j,t-1}(i) + x_{j,t}(i) \\ \text{inven}_{jt}(i) &\geq 0 \end{aligned} \tag{9}$$

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 CES technology:

$$y_{jt} \equiv \left[\int_0^1 \theta(i)(y_{jt}(i))^\rho di\right]^{\frac{1}{\rho}} \tag{10}$$

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 II. 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.

S1.A.3 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 Section S1.A.5, and since entrepreneurs have identical first-order conditions, I suppress the notation of the entrepreneur, Ej.

The Euler equation for the entrepreneur is

$$\frac{1}{c_t^{\sigma_c}} = E_t \frac{\gamma R_t}{c_{t+1}^{\sigma_c}} + \eta_t \tag{11}$$

where η_t is the Lagrange multiplier associated with the borrowing constraint (equation (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 entrepreneur j is

$$w_t = (1-\alpha)\frac{x_{jt}R^I(\theta_{jt}^*)G(\theta_{jt}^*)^{\frac{1-\rho}{\rho}}}{l_t}\left\{\frac{\sigma_f-1}{\sigma_f}p_{jt}\right\} \tag{12}$$

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 Section S1.A.5.

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

$$\frac{R^I(\theta_{jt}^*)G(\theta_{jt}^*)^{\frac{1-\rho}{\rho}}p_{jt}}{c_t^{\sigma_c}} = \gamma R^I(\theta_{jt}^*)E_t\left\{\frac{R^I(\theta_{j,t+1}^*)G(\theta_{j,t+1}^*)^{\frac{1-\rho}{\rho}}p_{j,t+1}}{c_{t+1}^{\sigma_c}}\right\} \tag{13}$$

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

S1.A.4 Calibration and Results

The calibration of parameters is standard, as in Table S.1. I assume that $\theta(i)$ is drawn from the Pareto distribution: $F(\theta) = 1-\left(\frac{1}{\theta}\right)^{\xi}$. $\bar{b}_t$ follows an exogenous AR(1) process $\ln(\bar{b}_t) = \rho^{\bar{b}}\ln(\bar{b}_{t-1}) + \varepsilon_t^{\bar{b}}$, where $\sigma_{\bar{b}}$

is the standard error of the $\varepsilon_t^{\bar{b}}$. The calibration of inventory parameters (ξ and ρ) follows Wen (2011) and matches the inventory-investment-to-GDP ratio of 0.01 and the inventory-to-sales ratio of 1. The demand elasticity of substitution is calibrated based on the median value of the estimated elasticity used in Section IV.B

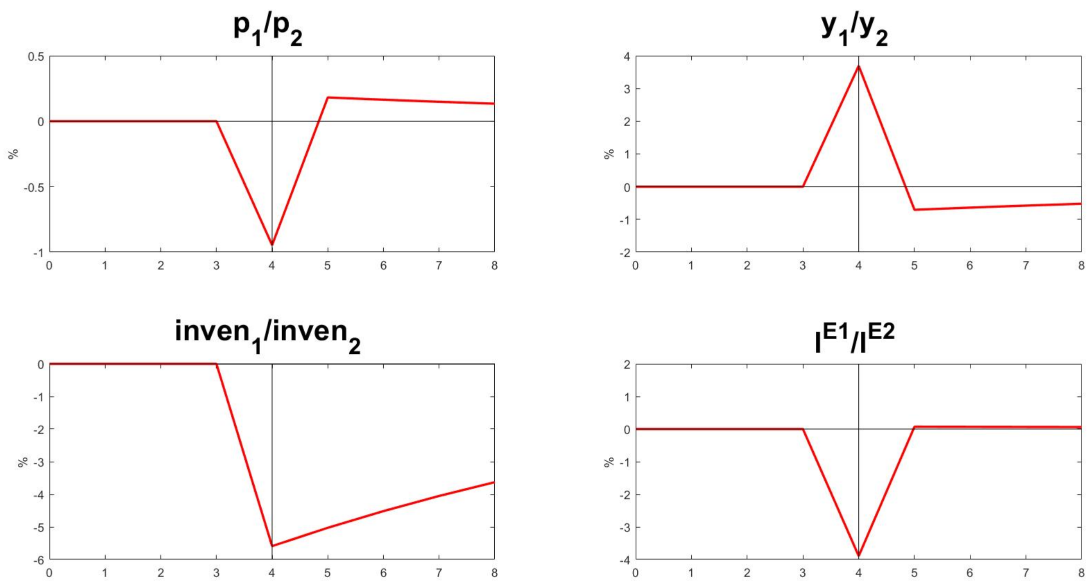
TABLE S.1: CALIBRATION

Simple general equilibrium model in section S1.A		
Parameter	Meaning	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
σ_f	Demand elasticity of substitution (producer)	3.9
$\rho^{\bar{b}}$	Borrowing shock parameter	0.95
$\sigma_{\bar{b}}$	Borrowing shock parameter	1
Extended general equilibrium model in section S1.B		
Parameter	Meaning	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

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 she wants to smooth 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 S.1 shows the impulse response function of the relative output price, inventory, market share, and employment. The model generates a temporary decrease in the relative output price, as shown in Table IV and Figure III. This relative price dynamics occurs because entrepreneur 1 decreases employment and production but increases sales as she draws down inventory, consistent with Table V.

FIGURE S.1: 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.

S1.A.5 Derivation of Entrepreneur-Level Optimality Conditions

Denote $x_{jt} \equiv \int_0^1 x_{jt}(i)di$, $s_t \equiv \text{inven}_t$ and $\{\lambda_{1,t}, \eta_t, \lambda_{3,t}, \lambda_{2,t}(i), \xi_t(i)\}$ as the non-negative Lagrangian multipliers for the constraints (6)-(9), respectively. For simplicity, suppress the notation for entrepreneurs Ej since the solution is identical. The first-order conditions for $\{c_t, b_t, l_t, y_{jt}(i), x_{jt}(i), s_{jt}(i), c_{1t}, c_{2t}\}$ are

$$\frac{1}{c_t^{\sigma_c}} = \lambda_{1,t} \tag{14}$$

$$\lambda_{1,t} - \eta_t - \gamma E_t \lambda_{1,t+1} R_t = 0 \tag{15}$$

$$\lambda_{1,t} w_t = \lambda_{3,t}(1-\alpha)\frac{x_t}{l_t} \tag{16}$$

$$\lambda_{1,t}\frac{\sigma_f - 1}{\sigma_f} y_{jt}^{\frac{\sigma_f - 1 - \rho\sigma_f}{\sigma_f}} y_t^{\frac{1}{\sigma_f}} \theta_t(i) y_t(i)^{\rho-1} = \lambda_{2,t}(i) \tag{17}$$

$$\lambda_{3,t} = E_t^i \lambda_{2,t}(i) = \int \lambda_{2,t}(i) dF(\theta_t) \tag{18}$$

$$\lambda_{2,t}(i) = \gamma E_t \lambda_{2,t+1}(i) + \xi_t(i) \tag{19}$$

plus the relevant transversality conditions and the complementarity slackness condition, $s_t(i)\xi_t(i) = 0$, for all $i \in [0,1]$. Notice that equation (18) 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. By using the iterated expectation,

$$\lambda_{2,t}(i) = \gamma E_t \lambda_{3,t+1} + \xi_t(i) \tag{20}$$

There are 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 (9) implies that $y_{jt}(i) \leq x_{jt}(i) + s_{j,t-1}(i)$. Because equation (17) implies $y_{jt}(i) =$

$\left[\frac{\lambda_{1,t}\frac{\sigma_f-1}{\sigma_f}y_{jt}^{\frac{\sigma_f-1-\rho\sigma_f}{\sigma_f}}y_t^{\frac{1}{\sigma_f}}\theta_t(i)}{\gamma E_t\lambda_{3,t+1}}\right]^{\frac{1}{1-\rho}}$, we have $\theta(i) \leq \left[x_{jt}(i)+s_{j,t-1}(i)\right]^{1-\rho}\left[\frac{\gamma E_t\lambda_{3,t+1}}{\lambda_{1,t}\frac{\sigma_f-1}{\sigma_f}y_{jt}^{\frac{\sigma_f-1-\rho\sigma_f}{\sigma_f}}y_t^{\frac{1}{\sigma_f}}}\right] \equiv \theta^*$, which defines the optimal cutoff value θ^* and the optimal stock as $x_{jt}(i)+s_{j,t-1}(i) \equiv \left[\frac{\lambda_{1,t}\frac{\sigma_f-1}{\sigma_f}y_{jt}^{\frac{\sigma_f-1-\rho\sigma_f}{\sigma_f}}y_t^{\frac{1}{\sigma_f}}\theta^*}{\gamma E_t\lambda_{3,t+1}}\right]^{\frac{1}{1-\rho}}$.

- CASE B: In the case where $\theta(i) > \theta^*$, we have $\xi_t(i) > 0$, $s(i) = 0$, and $y_{jt}(i) = x_{jt}(i)+s_{j,t-1}(i) \equiv \left[\frac{\lambda_{1,t}\frac{\sigma_f-1}{\sigma_f}y_{jt}^{\frac{\sigma_f-1-\rho\sigma_f}{\sigma_f}}y_t^{\frac{1}{\sigma_f}}\theta^*}{\gamma E_t\lambda_{3,t+1}}\right]^{\frac{1}{1-\rho}}$. Equation (17) then implies that $\lambda_{2,t}(i) = \gamma E_t\lambda_{3,t+1}\frac{\theta_t(i)}{\theta^*} > \gamma E_t\lambda_{3,t+1}$.

Given these two possibilities, equation (18) can be written as

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

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 the aggregate variables are independent of idiosyncratic shocks, equation (21) can be written as

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

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 (22) solves the optimal cutoff value as $\theta_t^* = (R^I)^{-1}(\lambda_{3,t}/\gamma E\lambda_{3,t+1})$. The decision rules for $x_{jt}(i)$ are given by

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

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

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

The shadow price of inventory i is determined by

$$\lambda_{2,t}(i) = \gamma E_t \lambda_{3,t+1} \times \max\left\{1, \frac{\theta(i)}{\theta^*}\right\} \tag{26}$$

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 (23)-(25) under the law of large numbers gives

$$Y_{jt} = \left[\frac{\lambda_{1,t} \frac{\sigma_f - 1}{\sigma_f} y_{jt}^{\frac{\sigma_f - 1 - \rho\sigma_f}{\sigma_f}} y_t^{\frac{1}{\sigma_f}}}{\gamma E_t \lambda_{3,t+1}}\right]^{\frac{1}{1-\rho}} D(\theta_t^*) \tag{27}$$

$$x_{jt} + s_{j,t-1} = Y_{jt} \frac{D(\theta_t^*) + H(\theta_t^*)}{D(\theta_t^*)} \tag{28}$$

$$s_{jt} = Y_{jt} \frac{H(\theta_t^*)}{D(\theta_t^*)} \tag{29}$$

and combining and aggregating the first-order conditions (26) and (17) lead to

$$\lambda_{3,t} = \lambda_{1,t} R^I(\theta_t^*) G(\theta_t^*)^{\frac{1-\rho}{\rho}} \left\{\frac{\sigma_f - 1}{\sigma_f} \left(\frac{y_t}{y_{jt}}\right)^{\frac{1}{\sigma_f}}\right\} \tag{30}$$

where

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

The entrepreneur-level budget constraint (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 hypothetical relative price of intermediate goods with respect to the final good.

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

$$\frac{1}{c_t^{\sigma_c}} = E_t \frac{\gamma R_t}{c_{t+1}^{\sigma_c}} + \eta_t \tag{31}$$

$$w_t = (1-\alpha) \frac{x_{jt} R^I(\theta_{jt}^*) G(\theta_{jt}^*)^{\frac{1-\rho}{\rho}}}{l_t} \left\{ \frac{\sigma_f - 1}{\sigma_f} p_{jt} \right\} \tag{32}$$

$$\frac{R^I(\theta_{jt}^*) G(\theta_{jt}^*)^{\frac{1-\rho}{\rho}} p_{jt}}{c_t^{\sigma_c}} = \gamma R^I(\theta_{jt}^*) E_t \left\{ \frac{R^I(\theta_{j,t+1}^*) G(\theta_{j,t+1}^*)^{\frac{1-\rho}{\rho}} p_{j,t+1}}{c_{t+1}^{\sigma_c}} \right\} \tag{33}$$

$$c_{1t} = \left(\frac{p_{1t}}{p_t} \right)^{-\sigma_f} c_t, j = 1, 2 \tag{34}$$

$$c_{2t} = \left(\frac{p_{2t}}{p_t} \right)^{-\sigma_f} c_t, j = 1, 2 \tag{35}$$

where the equations correspond to the Euler equation (31), the labor demand (32), the inventory demand (33), the good 1 demand (34), and the good 2 demand (35).

The aggregate budget constraints are

$$c_t + w_t l_t + R_{t-1} b_{t-1} - b_t = p_{jt} \frac{y_{jt}}{Y_{jt}} \left[a_t (l_t)^{1-\alpha} + s_{j,t-1} - s_{jt} \right] \tag{36}$$

$$s_{jt} = Y_{jt} \frac{H(\theta_{jt}^*)}{D(\theta_{jt}^*)} \tag{37}$$

$$x_{jt} + s_{j,t-1} = Y_{jt} \frac{D(\theta_{jt}^*) + H(\theta_{jt}^*)}{D(\theta_{jt}^*)} \tag{38}$$

$$b_t = \bar{b}_t \tag{39}$$

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.

S1.B An Extended General Equilibrium Model

I extend the simple model in section S1.A by adding money, price rigidity, a central bank, and capital investment. The simple model 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 a central bank that follows the Taylor rule. I assume that the 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 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.[1] Type j retailers' optimal condition can be characterized by the following equation:

$$E_t \sum_{s=0}^{\infty} (\beta\phi)^s \frac{u'(c_{t+s})}{u'(c_t)} \left(\frac{p_{jt}(z)}{p_{t+s}} - \frac{\varepsilon - 1}{\varepsilon} \frac{p^w_{j,t+s}}{p_{t+s}} \right) y_{j,t+s}(z) = 0 \tag{40}$$

where $p_{jt}(z)$ is the "reset" price, $p^w_{j,t+s}$ is the price that entrepreneurs charge to retailers, $y_{j,t+s}(z)$ 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:

$$R_t = (R_{t-1})^{r_R} (\pi_{t-1}^{1+r_\pi} (y^{\text{GDP}}_{t-1}/y^{\text{GDP}})^{r_Y} \bar{rr})^{1-r_R} e_{R,t} \tag{41}$$

where R_t is the interest rate at time t and y^{GDP}_t is total production in the economy at time t. I allow for persistence in the interest rate R_t and calibrate the parameters by 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 (6).

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

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

where I_{jt} is the 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 $\Psi(k_{jt}, k_{j,t-1})$ is a quadratic adjustment cost that 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 consumption without changing the output price. This capital is used in production and the production function (8) is replaced by the following equation

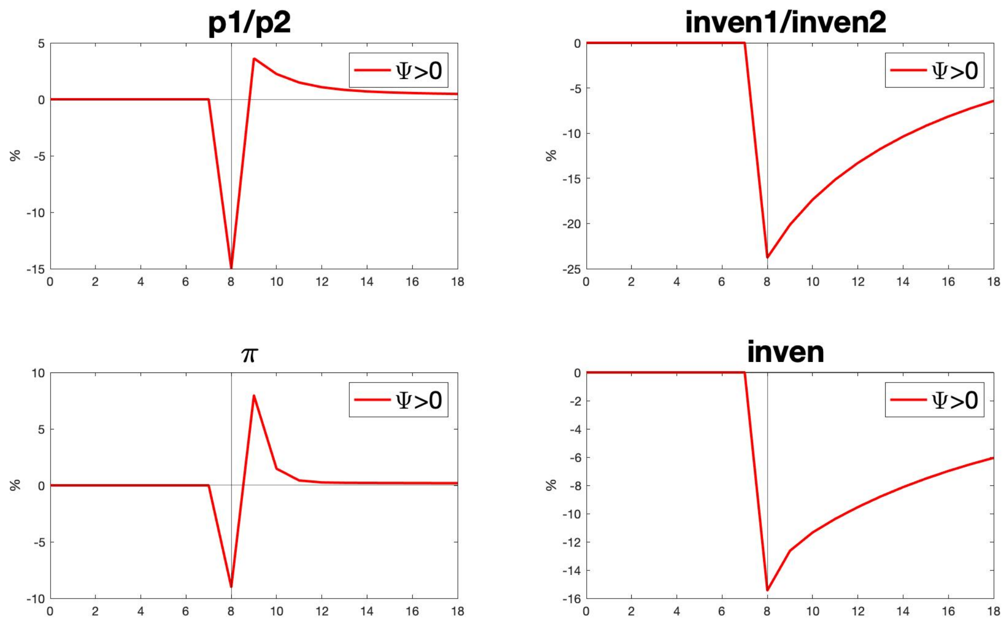
$$\int_0^1 x_{jt}(i)di = k_{jt}^{\alpha} l_{jt}^{1-\alpha} \tag{42}$$

The key parameter in this setup is the capital adjustment cost. In the benchmark case, I assume that the capital adjustment cost parameter, ψ_k, equals 15. This parameter is large enough such that entrepreneurs cannot disinvest sufficient 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 counter-factual 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 is 0 otherwise. This result is reported in Section S8. The calibration of other parameters in the extended model is standard, as in Table S.1. The parameters in the Taylor rule follow Iacoviello (2005), and the demand elasticity across products follows the median value used in Section IV.B. 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 who faces a temporary shock accumulates inventory immediately in the next period, whereas an entrepreneur who faces a persistent shock slowly stocks inventory.

Based on the benchmark calibration, I find that a drop in entrepreneur 1's borrowing capability leads to a decrease in the relative price and inventory and a drop in *aggregate* inflation and inventory. The results are reported in Figure S.2. A decrease in the relative variables in this model is consistent with the micro-level empirical analysis, which is the same as the simple model presented in Section S1.A. At the same time, this model generates a large decrease in aggregate inflation and inventory dynamics. Both the 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, which leads both the relative price and aggregate inflation to increase.

In addition, since the economy is characterized by the liquidity trap in the Great Recession, I make a parsimonious change in the model to integrate the idea of the zero lower bound. To reflect the fact that the central bank does not have control over the interest rate, I fix the interest rate for four quarters when the tightening of the borrowing constraint occurs. After four quarters, I allow the central bank to target the interest rate that follows Equation (41). Figure S.3 shows the results. When the credit supply shock on

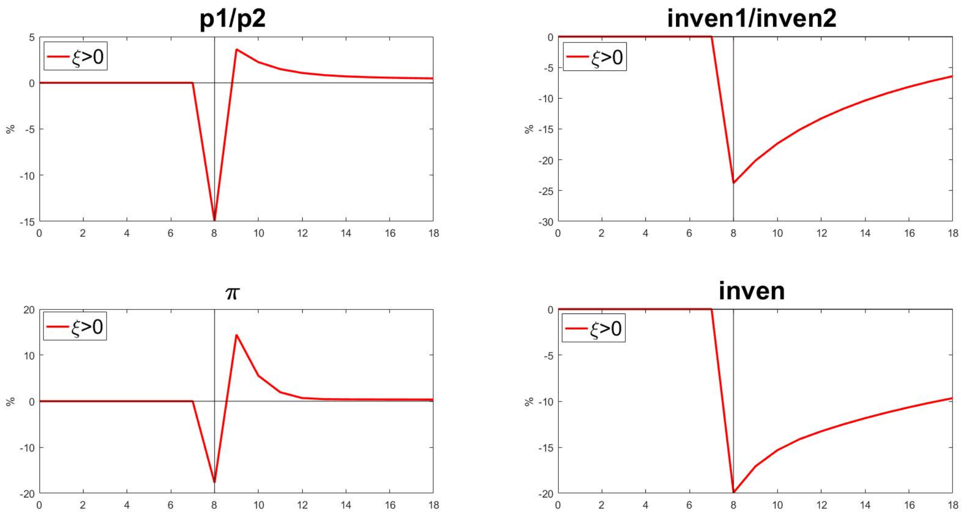
FIGURE S.2: AGGREGATE AND DIFFERENTIAL RESPONSE OF PRICE AND INVENTORY WITH RESPECT TO THE NEGATIVE CREDIT SUPPLY SHOCK



Note. The top-left panel shows the dynamics of the 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.

FIGURE S.3: AGGREGATE AND DIFFERENTIAL RESPONSE OF PRICE AND INVENTORY, FIXING INTEREST RATE

WITH RESPECT TO THE NEGATIVE CREDIT SUPPLY SHOCK



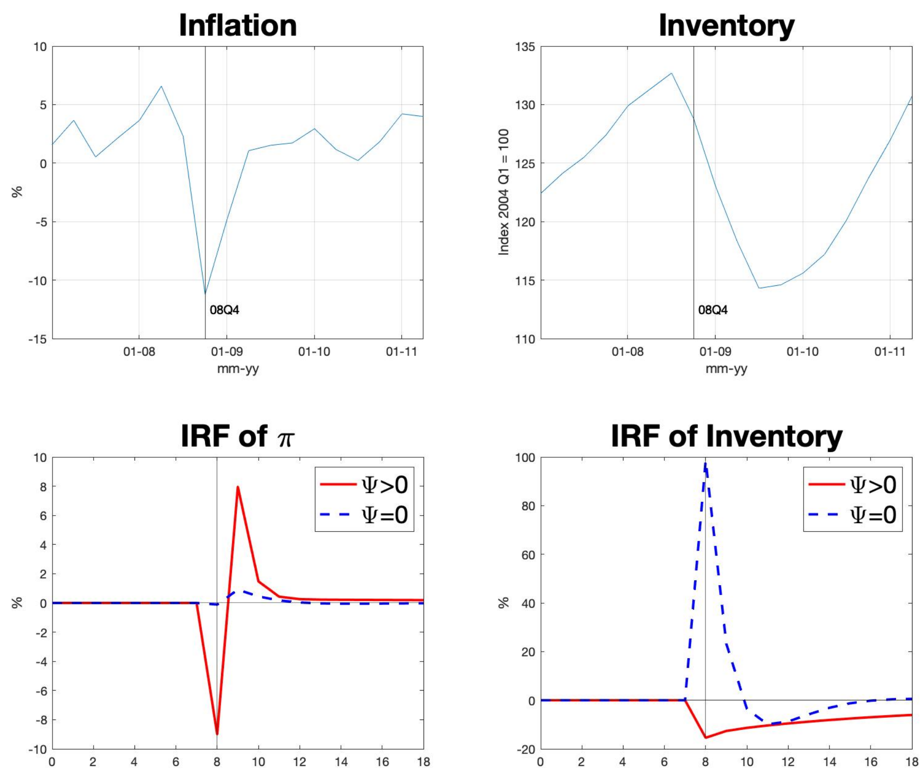
Note. The top-left panel shows the dynamics of relative output price, the top-right panel shows the dynamics of relative inventory, the bottom-left panel shows the dynamics of aggregate inflation, and the bottom-right panel shows the dynamics of average inventory due to the negative credit supply shock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

entrepreneur 1 reduces the aggregate inflation dynamics, the central bank does not have the power to lower the interest rate to stabilize the inflation, which leads to a larger drop in the aggregate inflation. Similarly, in the subsequent period, the central bank cannot stabilize the inflation, which makes the aggregate inflation to overshoot even more relative to the conventional monetary policy. Although this extension of the model is not the micro-foundation of the zero lower bound, this exercise suggests that the liquidity trap would likely amplify the effect of the inventory adjustment mechanism on the aggregate inflation dynamics in this period.

Lastly, I compare the impulse response generated from the model with the U.S. producer price index and inventory data, as shown in Figure S.4. For this exercise, I let the central bank follow the standard Taylor rule; fixing the interest rate only magnifies the change in the aggregate inflation dynamics. The aggregate inflation dynamics in Figure S.4 replicates Figure V. 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 9% drop in the output price. This drop in inflation explains approximately 80% 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 in inflation is consistent with previous studies that generate the inflationary forces with respect to the credit supply shock. I then 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 S.4, aggregate inflation does not change much in this case, because the entrepreneur can smooth 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, which gives an incentive to hoard inventory at the time of the shock 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, which leads to greater inefficiency for the entrepreneur. Overall, this comparison shows the importance of the fire sale of inventory mechanism; without the fire sale of inventory, there is no dramatic change in the inflation dynamics in the model, which is inconsistent with the data under the assumption that the credit supply shock is important in explaining aggregate variable dynamics.

FIGURE S.4: 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.

S1.C An Analytical Example of a Partial Equilibrium Model

This section presents a simple analytical example of the model in Alessandria, Kaboski, and Midrigan (2010).[2] The model can capture the gradual increase in the output price due to the decrease in inventory stock. I illustrate the ideas with the key equations, whereas the Online Appendix of Alessandria, Kaboski, and Midrigan (2010) experiments in detail with the effect of a permanent increase in real interest rates on output prices through the inventory adjustment.

Consider a retailer that resells ordered storable input with a one-period lag in a monopolistic competitive market. Due to the lag, the inputs are stored in inventory before they can be sold on the market, and they face depreciation costs of inventory. Retailers cannot sell more than what they have in inventory, and the ordered inputs are irreversible. Assume that retailers face a static CES demand system:

$$q = p^{-\theta} \tag{43}$$

where q is quantity sold, p is the price that a retailer sets, and θ is the demand elasticity parameter. Given the demand condition, retailers maximize profit by choosing how many quantities they sell and how many inputs they order. Under these conditions, the retailer's problem is

$$V(s;\omega) = \max_{q,i} \left(q^{\frac{\theta-1}{\theta}} - \omega i \right) + \beta V((1-\delta)(s-q+i)) \tag{44}$$

subject to

$$\begin{aligned} q &\leq s \\ 0 &\leq i \end{aligned} \tag{45}$$

where s is inventory, ω is an input price, i is an input, and δ is a depreciation rate. $q \leq s$ is the condition that the goods sold cannot exceed the inventory that the retailer has, and $0 \leq i$ is the irresponsibility condition. By forming the Bellman equation and solving the problem to get the first order conditions,

$$\underline{V}(s;\omega) = \max_{q,i} \left(q^{\frac{\theta-1}{\theta}} - \omega i \right) + \beta V((1-\delta)(s-q+i)) + \lambda(s-q) + \mu i \tag{46}$$

$$q : \frac{\theta-1}{\theta} q^{-\frac{1}{\theta}} = \beta(1-\delta)V'(s') + \lambda \tag{47}$$

2. This example builds on the analytical exercise explained by Geroge Alessandria in a discussion of the paper.

$$i : \omega = \beta(1-\delta)V'(s') + \mu \tag{48}$$

$$s : V'(s) = \beta(1-\delta)V'(s') \tag{49}$$

By rearranging the equations along with the demand condition, the optimal output price that retailers set with no capacity constraint ($\lambda = 0$) is the following:

$$p = \frac{\theta}{\theta - 1}(\omega - \mu) \tag{50}$$

If retailers order the input ($i > 0$ or $\mu = 0$), the output price is a conventional markup over the current input cost (or the replacement cost): $p = \frac{\theta}{\theta-1}\omega$. However, if retailers face an increase in the real interest rate that decreases the discount factor β, which effectively increases the cost of holding inventory, retailers are likely to decrease their inventory stock and less likely to order the input in this period ($i = 0$ or $\mu > 0$). In this case, the output price can fall below the conventional markup over the current input cost.

And the output price in the next period relative to the price in this period becomes

$$\frac{p'}{p} = \frac{1}{\beta(1-\delta)} \tag{51}$$

where p' is the price in the next period. Note that if β falls due to an increase in the real interest rate, the relative price rises. Moreover, the price rises gradually in this case as retailers run down their inventory stock.

S2 Price vs. Quality-Variety

This section leverages the nested-CES demand system presented in the Appendix to exactly decompose the price index and the market share into two margins: the conventional price margin and the quality-variety margin. Then I regress each margin on the credit supply shock to decompose the effect of the credit supply shock.

S2.A Price Index Decomposition: Price vs. Quality-Variety

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—crucially depends 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. The firms that face a negative credit supply shock might decrease their output price index by increasing the number of products (by drawing down the 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 shown in the Appendix, 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 S.2, in which the first 6 regression results replicate the results in Table IV. 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 the 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 VI and Section S1.

S2.B Market Share Decompostion: Price vs. Quality

This section shows the role of product quality in explaining the change in market share. Although Section S2.A presents the minor role of product quality in explaining the change in output prices, such a quality change potentially has a large effect on the market share. The change in product quality can rationalize the large decrease in output price despite a small increase in market share, given the conventional measure of demand elasticity.

To clarify the role of product quality, I use the market share equation derived under the nested CES demand system in equation (14). By taking the log of the equation and first difference across the pre-Lehman and post-Lehamn periods, the equation becomes

$$\Delta \ln S_{fg} = \underbrace{(1-\sigma_g^F)\Delta \ln P_{fg}}_{(1)} - \underbrace{\left\{(1-\sigma_g^F)\Delta \ln \varphi_{fg} + \lambda_g\right\}}_{(2)} \tag{52}$$

where $\lambda_g \equiv \Delta \ln \left[\sum_{k\in\Omega_g}\left(P_{kg}/\varphi_{kg}\right)^{(1-\sigma_g^F)}\right]$. Note that the change in the log market share is exactly decomposed into two parts. The first part reflects the change in the firm-group-specific price index, and the effect of the change in price on the change in market share is governed by the demand elasticity. If the demand elasticity is 4, a 15-percent decrease in the output price leads to a 45-percent increase in the market share.[3] The second part reflects the change in product quality. If firm-group-level average product quality falls, such

3. Holding the product group-level sales (and the product quality) constant, the effect of the log price on the log market share is identical to the effect of the log price on log sales. Note that the increase in the market share is not 60 percent when the demand elasticity equals to 4, because the market share is defined in terms of sales, not quantity.

TABLE S.2: THE EFFECT OF THE CREDIT CRUNCH ON THE OUTPUT PRICE: DECOMPOSITION

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

	$\Delta \ln SD_{\text{fg}}$: 2006q4-2007q2 to 2008q4-2009q2					
	OLS		$(-\Delta L_f)$ instrumented using			
			Lehman	ABX	BankItem	All
$(-\Delta L_f)$	0.06	-0.14	0.31	0.26	-1.31	-0.39
	(0.32)	(0.86)	(0.98)	(1.12)	(1.40)	(0.86)
Firm-level controls	No	Yes	Yes	Yes	Yes	Yes
Product group FE	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			16.20	7.90	14.90	12.00
J-statstics p-value						0.49
$E[\Delta \ln SD_{\text{fg}}]$	0	0	0	0	0	0
$E[\Delta \ln SD_{\text{fg}}$:$(-\Delta L_{\text{p90}})$-$(-\Delta L_{\text{p10}})]$	.1	-.3	.7	.6	-2.9	-.9
Observations	1658	1658	1658	1658	1658	1658

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, the regression is weighted by initial sales, and the firm-level controls are the firm's listed status, 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 a decrease in quality leads to a decrease in the market share. The group-specific index, λ_g, also affects the firm-group-specific market share.

Equation (52) shows how the credit supply shock affects the market share and rationalizes both a large decrease in the output price and a small increase in the market share due to the negative credit supply shock. The firms that face a negative credit supply shock decrease their output prices, and the decrease clearly increases the market share. However, such a shock is also likely to decrease their product quality. The firms that cannot finance their products likely fail to keep up with high-quality goods, which requires a higher cost. In addition, it could be that such firms decrease their advertising expenditure, which, in turn, reduces consumers' preferences for their products.[4] As a result of the decrease in product quality, the market share would only increase moderately with a large decrease in the output prices.

By leveraging equation (52) and the product-group-specific estimated demand elasticity, I decompose the change in the log of market share exactly into two parts: the pricing part and the quality part. I regress each part of the market share on the credit supply shock, similar to what is in Hottman, Redding, and Weinstein (2016). In this analysis, I allow the product group fixed effect to absorb λ_g and to be consistent with the main regression analysis.

TABLE S.3: CHANGE IN MARKET SHARE: DECOMPOSITION

	(1)	(2)	(3)	(4)
Y_{fg}	ΔS_{fg}	$\Delta \ln S_{fg}$	$(1-\sigma_g^F)\Delta \ln P_{fg}$	$(1-\sigma_g^F)\Delta \ln \varphi_{fg} + \lambda_g$
(-ΔL_f)	2.44**	10.33	27.83**	-17.50
instrumented using Lehman	(1.19)	(19.63)	(13.26)	(23.61)
firm-level controls	Yes	Yes	Yes	Yes
product group FE	Yes	Yes	Yes	Yes
First-stage F statistics	18.90	18.90	18.90	18.90
$E[\Delta\text{Y}:\Delta L_{\text{p90}}\text{-}\Delta L_{\text{p10}}]$	5.3	22.4	60.4	-38
Observations	1658	1658	1658	1658

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

Table S.3 presents the results. Column (1) is the replication of Table V column (2) by using the change in market share as a dependent variable. An increase in the credit supply shock by one standard deviation leads to a decrease in the market share by approximately 2.4 percentage points. Column (2) uses the log change in market share instead of the change in market share to match equation (52). Although the coefficient is not statistically significant at the conventional level, there is an increase in the market share under the current specification. Columns (3) and (4) decompose the log change in market share into exactly two parts: the pricing part and the quality part. Based on the pricing part, there is a large increase in the market share due to the decrease in output prices. The 90-10 percentile ratio is around 60 percentage points. However,

4. Note that the quality is defined as what affects the market share condition on the output price. Thus, the concept of quality integrates not only the change in the intrinsic quality, such as the product attributes of firms, but also the perceived quality, such as the change in consumers' tastes due to the decrease in advertising.

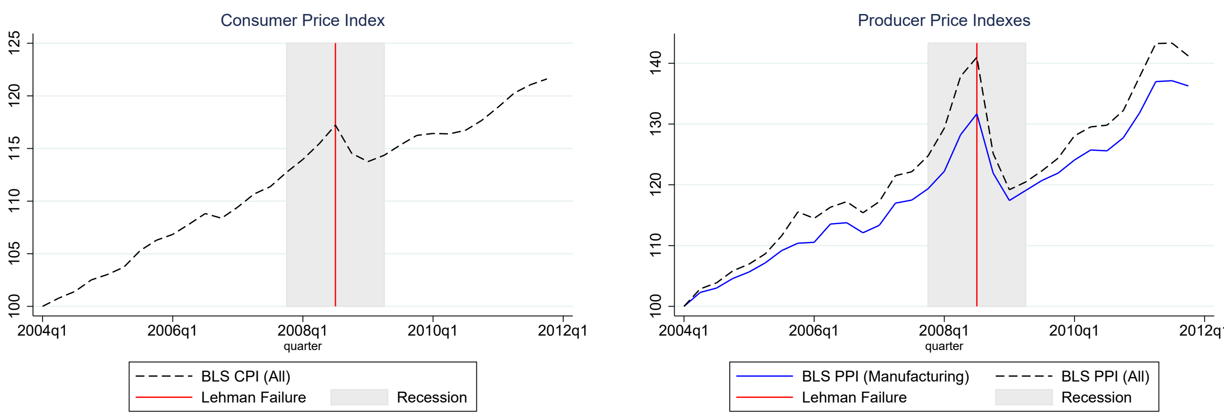
the quality part shows an economically large effect of the negative credit supply shock on product quality. Although the effect is not statistically significant at the conventional level, such a decrease in product quality counteracts the decrease in prices, which leads to a modest increase in the market share.

S3 Aggregate Price Indexes

This section presents the aggregate consumer, producer, manufacturing, and scanner price indexes in the middle of financial panic.

Figure S.5 plots the aggregate consumer and producer price indexes. As one can see, regardless of using different price indexes, the aggregate price index fell in the middle of financial panic. The decrease in the aggregate price indexes in the middle of financial panic was followed by a rise in the aggregate price index, which is consistent with the inventory adjustment hypothesis.

Figure S.5: Aggregate Price Indexes after the Lehman Failure



(a) Consumer price index

(b) Producer price indexes

Note. (a) plots the BLS aggregate consumer price index, and (b) plots the BLS aggregate producer price index and the producer price index for manufacturing sectors only. All the series are downloaded from the FRED Economic Data.

Of course, there are other reasons behind the movement in the aggregate price dynamics in this period in addition to the inventory adjustment hypothesis proposed in this article, such as the movement in aggregate demand conditions, uncertainty, international trade, and oil and commodity prices. In particular, there was a large decrease in oil and commodity prices at the same time. Given that the manufacturing price index fell dramatically simultaneously, the mechanical inclusion of oil/commodity price indexes cannot entirely explain the change in the aggregate PPI. However, such a change in the oil/commodity price indexes would likely pass-through to other indexes and generate a movement in the aggregate price dynamics. Other changes in the aggregate conditions, such as the aggregate demand changes, can potentially affect the aggregate inflation in this period. To isolate the effect of the credit supply shock on the output price dynamics, in the main body of the article, I use the micro-level data and utilize both cross-sectional variation and time-series variation.

S3.A Scanner Price Index

I measure the product group-quarter-specific price index by taking a geometric average of the firm-group-time-level price index ($\tilde{P}_{fgt}$) defined in equation (3) across firms within the product group and time:

$$\tilde{P}_{gt} = \left(\prod_{f \in \Omega_{gt}} \tilde{P}_{fgt} \right)^{1/N_{gt}} \tag{53}$$

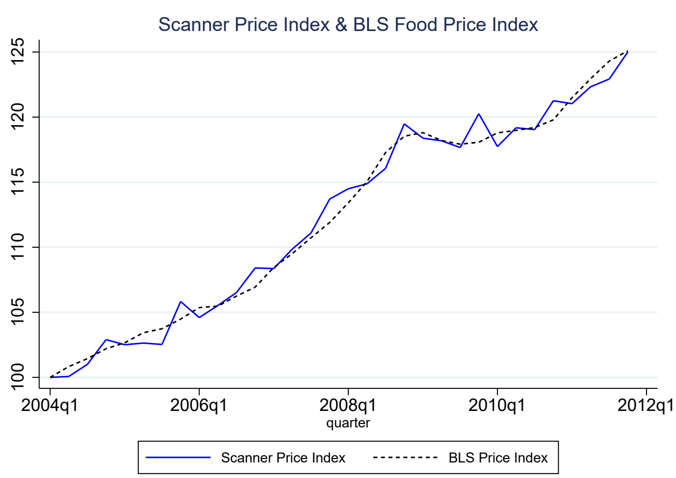
where Ω_{gt} is the set of the firms in product group g at time t, and N_{gt} is the number of firms in product group g at time t. Similar to the firm-group-level price index, this product group-level price index is the part of the nested-CES utility-based price index that does not adjust for a variety-quality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

$$\frac{\tilde{P}_t}{\tilde{P}_{t_0}} = \prod_{g \in \Omega} \left(\frac{\tilde{P}_{gt}}{\tilde{P}_{gt_0}} \right)^{(\varphi_{gt} + \varphi_{gt_0})/2}$$

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

To check the validity of the price index that I constructed, I plot the scanner price index with the BLS food price index. As shown in Figure S.6, the scanner price index closely follows the official price index.

FIGURE S.6: COMPARISON WITH THE OFFICIAL PRICE INDEX



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

S4 Further Data Description

This section further details the data used in this paper to complement Section II. First, I list the firms in the combined data. Second, I describe the Compustat data in detail, which is used to supplement the main findings of this article.

S4.A List of Firms in the Combined Data

Section II details how I combined different databases to conduct the empirical analysis. Table S.4 lists the largest 20 firms and the corresponding industry code present in the data. Since Nielsen does not allow me to reveal the particular retailer name, I conceal the name of retailers.

TABLE S.4: 20 Largest Companies

companyname	**naics code**	**rank by sales**
Retailer	4451	1
GENERAL MILLS INC	3112	2
Retailer	4451	3
CONAGRA FOODS, INC.	3114	4
KELLOGG COMPANY	3112	5
HERSHEY COMPANY (THE)	3113	6
J. M. SMUCKER COMPANY (THE)	3114	7
Retailer	4451	8
HEWLETT-PACKARD COMPANY	3341	9
S. C. JOHNSON & SON, INC.	3256	10
Retailer	4244	11
CHURCH & DWIGHT CO INC	3256	12
CLOROX CO	3256	13
COLGATE PALMOLIVE CO	3256	14
DEAN FOODS COMPANY	3115	15
INTERSTATE BAKERIES CORP	3118	16
GEORGIA-PACIFIC LLC	3222	17
3M COMPANY	3279	18
FLOWERS FOODS INC	3118	19
Retailer	4451	20

S4.B The Coverage of the Matched Sample

Table S.5 reports the coverage of the final matched sample used in this article. I restrict it to the observations that have non-missing sales for the last three-quarters of the pre-Lehman and the post-Lehman periods, as defined in Section II.B. The final matched sample covers approximately one-fifth of the total sales in the Nielsen data. Although the Nielsen-Orbis matched sample covers around 74 percent of the sales in the

ACNielsen Homescan Panel, when I restrict it to the firms that have valid information about employment and total assets, it covers approximately 23 percent of the sales in the Nielsen data.

TABLE S.5: THE COVERAGE OF THE MATCHED SAMPLE

	Final Matched Sample	Nielsen+Orbis, non-missing	Nielsen+Orbis	Nielsen
Value	124.67	144.68	461.36	624.07
Share	0.20	0.23	0.74	1

Note. The "Final Matched Samples" is the sample used to report Table I, "Nielsen+Orbis, non-missing" is the Nielsen-Orbis matched sample that has non-missing observations for total assets and employment for 2006 and 2008, "Nielsen+Orbis" is the Nielsen-Orbis matched sample, and "Nielsen" is the whole ACNielsen Homescan Panel data. Value is in billions of USD. Share corresponds to the share of values relative to the total sales value in the Nielsen data.

S4.C Compustat

In addition to the final combined sample, I supplement the data by using Compustat data. 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. It is widely used in the macroeconomics and finance research and collects information on firms mainly from SEC filings. I require firms to have a non-negative and non-missing measure of cash holdings. The data are useful in looking at the aggregate cyclicality of the corporate cash holdings, in reconciling the results with previous studies, in measuring Rajan and Zingales (1998) financial dependent index, and in investigating different types of inventory. The data that I use in this article are downloaded from Wharton Research Data Services (WRDS), and the cleaning of the data follows Bates, Kahle, and Stulz (2009). Below, I discuss how the Compustat data are used in the main body of this paper.

Figure IV uses Compustat data in looking at the cyclicality of the aggregate corporate cash holdings in the Great Recession. I only keep the U.S. firms that have positive values of corporate cash. In addition, I drop non-classifiable firms (SIC codes 9995, 9997, 9998), financial firms (SIC codes 6000-6999), and utilities (SIC codes 4900-4999). Financial firms might increase cash holdings to meet the capital requirement or for other non-economic factors. The cash holdings of firms in the utilities can be subject to regulatory supervision. In measuring the cash holding, I use cash and cash equivalent assets (the CHEQ variable in Compustat data). For the seasonal adjustment, I use the years from 1980-2006 and run the X-13ARIMA-SEATS Seasonal Adjustment Program available from the census. See https://www.census.gov/srd/www/x13as/ for more information.

Tables VII, VIII, and S.26 use Compustat data to measure control variables and to understand the behavior of the firms that have a large amount of cash in 2006. Since one exercise is the replication of Bates, Kahle, and Stulz (2009), I follow their cleaning carefully, such as winsorization of the variables. The firms that had an IPO within the past five years are dropped. The variables used are cash to assets, cash flow volatility, capital expenditure to assets, acquisition to assets, debt to assets, firm size, market to book ratio, networking capital to assets, a dividend dummy, and R&D to sales. The cash flow volatility is measured as

TABLE S.6: **SUMMARY STATISTICS, COMPUSTAT DATA**

Variables	**N**	**mean**	**sd**	**p50**	**min**	**max**
Panel A: Year 2006						
Cash to assets	3866	0.23	0.25	0.13	-0.00	1.00
Market-to-book ratio	3695	3.50	7.36	1.82	0.28	100.20
Cash flow volatility	3193	0.13	0.17	0.07	0.01	1.03
Capital expenditure to assets	3834	0.05	0.06	0.03	0.00	0.41
Acquisition to assets	3667	0.02	0.05	0.00	-0.01	0.35
Leverage	3629	0.20	0.21	0.14	0.00	0.99
Firm size	3866	0.50	2.71	0.72	-11.45	8.00
Networking capital to assets	3720	-0.16	1.13	0.03	-13.74	0.54
Dividend payout dummy	3865	0.25	0.43	0.00	0.00	1.00
R& D to sale	2346	0.58	2.75	0.05	0.00	41.39
Panel B: Year 2008						
Market-to-book ratio	3335	2.56	6.43	1.24	0.17	98.52
Cash flow volatility	2907	0.13	0.16	0.07	0.01	1.04
Capital expenditure to assets	3446	0.05	0.06	0.03	0.00	0.41
Acquisition to assets	3338	0.02	0.05	0.00	-0.01	0.35
Leverage	3268	0.22	0.23	0.17	0.00	1.00
Firm size	3490	0.62	2.76	0.88	-11.49	7.75
Networking capital to assets	3350	-0.15	1.03	0.03	-12.14	0.55
Dividend payout dummy	3488	0.26	0.44	0.00	0.00	1.00
R& D to sale	2124	0.65	3.28	0.05	0.00	42.65

Note. Cash flow volatility is the standard deviation of cash flow to assets for the past 10 years. Leverage is the long-term debt plus debt in current liabilities divided by book assets. Firm size is measured as the logarithm of book assets in 2004 dollars.

Operating Income Before Depreciation - Total Interest and Related Expense - Total Income Taxes - Dividend Incomes - Purchase of Common and Preferred Stock (OIBDP - XINT - TXT - DVC - PRSTKC). Given the cash flow to assets, I measure the standard deviation of this variable for the past ten years with the firms that appear at least three consecutive years. Leverage is the long-term debt plus the debt in current liabilities divided by book assets. Firm size is measured as the logarithm of book assets in 2004 dollars. The summary statistics of all the variables are reported in Table S.6.

In measuring the Rajan and Zingales industry-level financial dependent index, which is used in Table VI and Section S6.K, I follow Rajan and Zingales (1998) carefully. I measure the cash flow separately for different format codes. I subtract the cash flow from the capital expenditure and sum the subtracted measure across the years 1962-2009 within firms. I divide it by the similarly summed capital expenditure and take a median across firms within the 2-digit SIC industry code to construct the financial dependent index. Finally, I use the Compustat data to report the inventory information by different parts and to run the corresponding regression analyses in Section S5. I detail the analysis in Section S5.

S4.D Orbis

I mainly use the Orbis data to combine the price and quantity information from the ACNielsen data and the Dealscan data. Orbis data has matching software that allows matching companies based on their name, address, and industry information. There are five matching categories in Orbis data as follows: Not matched (automatic); To be validated (potential); To be validated (unlikely); Validated (automatic); Validated (from custom rules). In using the matched data, I only used the validated matched sample and hand-check all the matched results.

TABLE S.7: **SUMMARY STATISTICS, ORBIS-DEALSCAN**

variable	N	mean	sd	min	p25	p50	p75	max
Inventory growth	992	13	39	-182	-4	13	29	194
2006 inventory	992	522	1677	0	34	116	399	33685
Change in cash to assets	1286	-1	10	-99	-3	-0	2	65
2006 cash holdings	1286	379	1623	0	13	57	204	28896
Employment growth	1453	8	34	-198	-6	5	21	199
2006 employment	1453	15	62	0	1	3	10	1900

Note. Inventory growth and employment growth are measured by using the Davis-Haltiwanger growth rate. The 2006 inventory and cash holdings are measured in millions of USD, and the 2006 employment is measured in thousand people.

In supporting the inventory adjustment mechanism, the firm-level variables in the Orbis data are used, as in Table V. For the firm-level regression analyses, I rely on the Orbis-Dealscan matched sample, which is the superset of the Orbis-Dealscan-GS1-Nielsen matched sample. Table S.7 presents the summary statistics of inventory, cash holdings, and employment variables used in Table V.

S5 Inventory by Parts

The inventory variable used in the main body of this article is the total sum of different parts of inventory, such as final goods, materials and supplies, and work in progress. The Orbis data do not report the inventory information by different parts, and such data are rare.[5] To my knowledge, the only firm-level data in the U.S. that documents different parts of the inventory is the Compustat data. Thus, I combine Compustat data with the Dealscan database to study the relative importance of each part of the integrated inventory. In combining the database, I use a linkage table provided by Chava and Roberts (2008).

In general, the final good inventory is the most important component of the corporate inventory in this period. During the non-Lehman period (2006Q4-2007Q2), approximately 50% of inventory is final-good, around 22% of inventory is work in progress, and approximately 28% of inventory is raw materials in the Compustat-Dealscan matched sample. If I use all firms available in Compustat data, around 51% of inventory is final-good, around 21% of inventory is work in progress, and approximately 28% of inventory is raw materials. Table S.8 presents the summary statistics of the inventory information in the Compustat-Dealscan matched sample.

TABLE S.8: **Summary Statistics, Compustat-Dealscan**

variable	N	mean	sd	min	p25	p50	p75	max
ΔInv_f	695	4	39	-200	-14	5	25	198
ΔInv_f^f	695	2	21	-101	-6	2	11	118
ΔInv_f^{wi}	695	0	14	-99	-3	-0	4	110
ΔInv_f^{rm}	695	2	18	-93	-5	1	9	128
Inv_f	695	539	1350	0	47	141	451	17437
Inv_f^f	695	265	767	0	13	56	207	12895
Inv_f^{wi}	695	120	362	0	5	20	71	4854
Inv_f^{rm}	695	155	467	0	12	41	115	7607

Note. The Δ operator stands for the Davis-Haltiwanger growth rate that uses the pre-Lehman and post-Lehman periods. ΔInv_f is the growth rate of the total inventory and ΔInv_f^f, ΔInv_f^{wi}, and ΔInv_f^{rm} are the growth rate of final-good, work-in-progress, and raw materials inventory, respectively. Inv_f is the total amount of inventory in millions of USD, and Inv_f^f, Inv_f^{wi}, and Inv_f^{rm} are the level of final-good, work-in-progress, and raw materials inventory in pre-Lehman period, respectively.

Based on the new data, I find that the firms that face a negative credit supply shock decrease both their final good and raw materials inventory, and both parts of inventory contribute to the total reduction of inventory in a similar magnitude.[6] I use the same regression specification that I used in the main body of the

5. For example, both the manufacturing trade & inventory & sales report of the Census Bureau and the NBER-CES manufacturing data do not report the inventory information by separate parts.

6. To maximize the variation of the credit supply shock, I use the main measure of the credit supply shock instead of the instrumental variables that are likely to affect the subset of firms.

paper:

$$\Delta \text{Inv}_f = \lambda + \gamma(\text{-}\Delta L_f) + \theta X_f + \varepsilon_f \tag{54}$$

where ΔL_f is the credit supply shock constructed in the main body of the paper, and X_f is the vector of the corresponding firm-level control variables.

ΔInv_{fg} is the growth rate of total inventory. Since Compustat data record firm-level information in each quarter, I average the inventory variable within the post-Lehman (2008Q4-2009Q2) and pre-Lehman (2006Q4-2007Q2) periods to be consistent with the timing of the credit supply shock. Then, I measure the growth rate across these two periods: $\frac{\text{Inv}_{f,\text{crisis}} - \text{Inv}_{f,\text{non-crisis}}}{\frac{1}{2}(\text{Inv}_{f,\text{non-crisis}} + \text{Inv}_{f,\text{crisis}})}$, where Inv_{ft} is the level of total firm-level inventory at time t.[7] To understand which part of inventory contributes to the total corporate inventory growth, I exactly decompose the growth rate of total inventory into three different parts of inventory similar to what has been done in Broda and Weinstein (2010):

$$\Delta \text{Inv}_f = \Delta \text{Inv}_f^f + \Delta \text{Inv}_f^{wi} + \Delta \text{Inv}_f^{rm} \tag{55}$$

where ΔInv_f^f is the growth rate of final good inventory, ΔInv_f^{wi} is the growth rate of work-in-progress inventory, and ΔInv_f^{rm} is the growth rate of raw materials inventory.[8] By using the decomposition of the total inventory in equation (55), I regress each part of the corporate inventory on the credit supply shock. In this way, I not only analyze the effect of the credit supply shock on different parts of inventory but also quantify the contribution of each part of inventory to the total corporate inventory growth.

Table S.9 reports the results based on equation (54). Column (1) confirms and replicates the analysis in the main body of the paper with the new data. As one can see, even with different samples and different timing of the inventory growth, the firms that face a negative credit supply shock decrease their inventory.[9] Columns (2), (3), and (4) show the decomposition of the effect of the credit supply shock on different parts of inventory. The effect on final-good inventory accounts for approximately 47% of the effect on the total inventory, and the effect on raw material inventory accounts for around 50% of the effect on the total inventory. The effect on work-in-progress inventory is negligible and not statistically significant.

The decomposition results in Table S.9 inform which part of inventory firms adjust when they face a negative credit supply shock. Intuitively, to be consistent with the inventory and liquidity management

7. I defined the growth rate in this way to be consistent with the employment growth rate. Using the conventional measure of the growth rate does not make much difference in the results.

8. $\Delta\text{Inv}_f^f = \frac{\text{Inv}^f_{f,\text{crisis}} - \text{Inv}^f_{f,\text{non-crisis}}}{\frac{1}{2}(\text{Inv}_{f,\text{non-crisis}} + \text{Inv}_{f,\text{crisis}})}$, $\Delta\text{Inv}_f^{wi} = \frac{\text{Inv}^{wi}_{f,\text{crisis}} - \text{Inv}^{wi}_{f,\text{non-crisis}}}{\frac{1}{2}(\text{Inv}_{f,\text{non-crisis}} + \text{Inv}_{f,\text{crisis}})}$, $\Delta\text{Inv}_f^{rm} = \frac{\text{Inv}^{rm}_{f,\text{crisis}} - \text{Inv}^{rm}_{f,\text{non-crisis}}}{\frac{1}{2}(\text{Inv}_{f,\text{non-crisis}} + \text{Inv}_{f,\text{crisis}})}$, where Inv^f is final-good inventory, Inv^{wi} is work-in-progress inventory, and Inv^{rm} is raw material inventory. Although I hold the denominator fixed across different dependent variables for the exact decomposition, using different parts of inventory in the denominator of the growth rates does not make much difference in the relative importance of the different parts of inventory.

9. There are three other differences relative to what is presented in the main table. First, I do not include bond access as a control since it is non-trivial to match bond market information here. Second, the firm in the data is defined based on the gvkey firm identifier available in the Compustat data to make everything coherent. Third, as discussed before, I am using the main credit supply shock measure. The relative importance of different parts of inventory is robust to different specifications.

TABLE S.9: THE EFFECT OF THE CREDIT CRUNCH ON INVENTORY: DECOMPOSITION BY PARTS

	(1)	(2)	(3)	(4)
	ΔInv_f	ΔInv_f^f	ΔInv_f^{wi}	ΔInv_f^{rm}
$(-\Delta L_f)$	-10.3***	-4.8***	-0.3	-5.2***
	(2.6)	(1.4)	(0.8)	(1.3)
firm-level controls	Yes	Yes	Yes	Yes
$E[\Delta y : \Delta L_{\text{p90}}\text{-}\Delta L_{\text{p10}}]$	-15.3	-7.1	-.4	-7.8
Observations	693	693	693	693

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by the three-digit NAICS, the regression is weighted by initial Inv_f, and the firm-level controls are the firm's listed status, two-digit NAICS FE, number of loans, multi-lead FE, loan spread, and number of loans due in the post-Lehman FE.

hypothesis proposed in the paper, the firms that face a negative credit supply shock would be most likely to liquidate the most liquid inventory. Since both the final-good inventory and the raw material inventory are more liquid relative to the work-in-progress inventory, they would liquidate such types of inventories. The results in Table S.9 are generally consistent with the inventory adjustment mechanism proposed in the main body of the paper.

S6 ROBUSTNESS CHECKS

This section reports various robustness checks conducted in this article.

S6.A 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 pre-treatment 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. However, excluding this period raises questions about what occurred to the 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 I ensures that this period is characterized by a shift in credit supply, Duchin, Ozbas, and Sensoy (2010) indicate that demand-side factors became more important during this period.[10] 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.

10. However, in choosing the post-treatment period, Duchin, Ozbas, and Sensoy (2010) examine the relationships among corporate investment, Tobin's Q, cash flow, and initial corporate cash holdings, not the variables related to the credit market. In particular, the bank shock I use generates an entirely different variation than the initial cash holdings.

I utilize three other definitions of pre- and post-treatment periods that incorporate 2007:Q4 to 2008:Q2 to corroborate the empirical findings, as shown in Table S.10. The first two columns report the results by defining 2007:Q4 to 2008:Q2 as the post-treatment period. By 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 a moderate degree of credit market stress, consistent with the external validity check in Section S6.K. In addition, given moderately 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, which additionally validates the measure of the Lehman failure. In addition, I define 2007:Q4 to 2008:Q2 as the pre-Lehman period and find that the effect of a credit supply shock on price is even stronger than it is in the main regression analysis.

TABLE S.10: 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.

S6.B Retailer Behavior

In this section, I address the 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. Although a 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.

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 the manufacturers that face a negative credit supply shock decrease their output prices, the 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 the manufacturers that face 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 main 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.[11] In my main regression analysis, I use a nested CES demand system across all UPCs and firms in the data and therefore 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. Although 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 that I constructed, which generates bias in the coefficient. Accordingly, I explicitly allow a retail store dimension in the data and remove all retail-level characteristics from the regression analysis.

Table S.11 reports the results. Because I allow retail store fixed effects, the credit supply shock measured at the retail level cannot be used. As one can see, despite the fact that I absorb retail-level variations, I still find that the firms that face a negative credit supply shock decrease their output prices. Note that the estimated coefficients are approximately 3% to 5%, which is smaller than the estimates reported in Table IV. 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 the manufacturers that must pass through retailers to sell their products to households. If incomplete pass-through exists at the retail level, the estimated coefficients must be smaller, which is indeed what I observe.

In addition, I use only the companies that are classified as retailers according to the NAICS industry code and find an even stronger result. Table S.12 reports the results. Despite the smaller number of observations, based on the main measure of credit supply shock, I still find that the firms that face a negative credit supply shock decrease their output prices. The magnitude of the coefficients is larger than the magnitude of coefficients reported in Table IV, which again suggests the possibility that incomplete pass-through causes the coefficient in the main analysis to be underestimated. Using bank statement items as an instrumental variable generates consistent coefficients. Using Lehman or ABX securities exposure as instruments generates larger

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

TABLE S.11: ROBUSTNESS: RETAIL STORE FIXED EFFECTS

	(1)	(2)	(3)	(4)	(5)
	$\Delta\ln P_{\text{fgr}}$: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, the regression is weighted by initial sales, the 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.

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. The 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 Promodata, which is also available from the Kilts Marketing Data Center to confirm the empirical findings. These data provide detailed competitive manufacturer cost 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, by using these data, I still find that the firms that face a negative credit supply shock decrease their output prices, as reported in Table S.13. The magnitude of the coefficient is again larger than the magnitude of the coefficient in Table IV, which suggests that incomplete pass-through exists. Using ABX securities as instruments generates large and statistically significant estimates, which suggests that the firms that face this particular shock decrease their prices even more. Using Lehman exposure or bank statement items as instruments generates negative but statistically insignificant results, which are likely a result of the weak instrument problem.

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 IV are likely to be the most conservative estimates because of incomplete pass-through. The 90th-10th percentile ratio is approximately 30% based on Tables S.12 and S.13, which

TABLE S.12: ROBUSTNESS: RETAILERS ONLY

	(1)	(2)	(3)	(4)	(5)
	$\Delta\text{lnP}_{\text{fg}}$: 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
$E[\Delta\text{lnP}:\Delta L_{\text{p90}}-\Delta L_{\text{p10}}]$	-27.5	-135	-113.6	-29.8	-32.4
Observations	763	763	763	763	763

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group; and the 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 S.13: 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
$E[\Delta\text{lnP}:(-\Delta L_{\text{p90}})-(-\Delta L_{\text{p10}})]$	-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.

suggests that the effect should be even larger once I control for retail-level variation. Overall, I conclude that retail-level output price variation does not alter the main findings.

S6.C 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, Rao, and Sufi (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, 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 that arise 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 the firms that face a negative credit supply shock increase their market share, as shown in Table V. Because a negative product demand shock leads to a decrease in the market share, these results show that the variation in the measure of the credit supply shock is not driven by the product demand shock. Moreover, the results are robust to controlling the initial inventory-sales ratio, which may be correlated with the negative demand shock, as shown in Table VII.

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 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 S.14 reports the results with purchaser information. I include purchasers' income, employment, race, age, education, housing price, and home ownership—the characteristics that are most likely to be affected by or sensitive to shocks during this period. The first two columns report the results with the

TABLE S.14: THE EFFECT OF THE CREDIT CRUNCH ON THE OUTPUT PRICE: PURCHASER CHARACTERISTICS

	(1)	(2)	(3)	(4)
	$\Delta \ln P_{fg}$: 2006q4-2007q2 to 2008q4-2009q2			
	OLS	IV All	OLS	IV 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
$E[\Delta \ln P]$	11.3	11.3	11.3	11.3
$E[\Delta \ln P$:$(-\Delta L_{p90})$-$(-\Delta L_{p10})]$	-18.7	-14.3	-17.1	-14.8
Observations	1673	1673	1673	1673

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, the regression is weighted by initial sales, and the firm-level controls are the firm's listed status, 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 $\Delta \ln P_{fg}$. The 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. A Cragg-Donaldson F-statistics is used for the first-stage F statistics.

pre-Lehman purchaser characteristics, and the last two columns report the results with a change in purchaser characteristics. Regardless of using two different specifications, the estimated coefficients are negative and statistically significant with the purchaser characteristics.

I also confirm my results by allowing the state dimension in the data with state fixed effects.[12] 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 S.15, I still find that the 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.

TABLE S.15: THE EFFECT OF THE CREDIT CRUNCH ON THE OUTPUT PRICE: STATE FIXED EFFECTS

	(1)	(2)	(3)	(4)	(5)
	$\Delta\ln\tilde{P}_{\mathrm{fgs}}$: 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
$E[\Delta\ln\mathrm{P}]$	10.9	10.9	10.9	10.9	10.9
$E[\Delta\ln\mathrm{P}$:$(-\Delta L_{\mathrm{p90}})$-$(-\Delta L_{\mathrm{p10}})]$	-10.1	-8.5	-21.2	-9.4	-12.3
Observations	26894	26894	26894	26894	26894

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, the regression is weighted by initial sales, and the firm-level controls are the firm's listed status, 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.

S6.D Foreign Exposure

One concern regarding the regression analysis is a large change in the overall international exposure in this period. If the firms that face a large negative credit supply shock are the firms 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 by 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 the number of foreign subsidiaries by total subsidiaries and the number of foreign branches by total branches and include these measures in the regression. As shown in

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

Table S.16, these variables do not seem to correlate with output price change, and the effect of credit supply shock on the output price is robust to adding these control variables.

TABLE S.16: THE EFFECT OF THE CREDIT CRUNCH ON OUTPUT PRICE: FOREIGN EXPOSURE

	(1)	(2)	(3)	(4)	(5)
	$\Delta\ln\tilde{P}_{\mathrm{fgs}}$: 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
$E[\Delta\ln\mathrm{P}]$	11.4	11.4	11.4	11.4	11.4
$E[\Delta\ln\mathrm{P}$:$(-\Delta L_{\mathrm{p90}})$-$(-\Delta L_{\mathrm{p10}})]$	-17.3	-13.7	-14.1	-16.2	-14.9
Observations	1658	1658	1658	1658	1658

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, the regression is weighted by initial sales, and the 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 the post-Lehman FE, spread, maturity, and a lagged dependent variable

S6.E 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 2018). Additionally, I used a different regression weight as a robustness test and report the result in Table S.17. The first three columns use the number of buyers as a weight and gives larger weight to the firm and group that matter the most to consumers. I also used the number of products in each bin as a weight, which replicates the UPC-level regression. Regardless of the weighting, I find that the firms that face a negative credit supply shock decrease their output prices relative to their counterparts.

S6.F 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 by using two variants of the measure of credit supply shock, ΔL_f.

TABLE S.17: THE EFFECT OF THE CREDIT CRUNCH ON OUTPUT PRICE: DIFFERENT WEIGHTINGS

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\text{lnP}_{\text{fg}}$: 2006q4-2007q2 to 2008q4-2009q2					
weight	Number of buyers			Number of UPCs		
	OLS		IV	OLS		IV
			Lehman			Lehman
$(-\Delta L_f)$	-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
$E[\Delta\text{lnP}]$	12.5	12.5	12.5	12	12	12
$E[\Delta\text{lnP}:(-\Delta L_{\text{p90}})\text{-}(-\Delta L_{\text{p10}})]$	-5	-19.7	-15.5	-5.1	-12.7	-14.9
Observations	1658	1658	1658	1658	1658	1658

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, the standard errors are clustered by firm and product group, the regression is weighted by initial sales, and the 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.

First, in constructing a change in bank health at the bank level (leave-one-out), I use the change in the number of loans per bank to measure the credit supply shock rather than the change in the amount of loans. Using the 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). Although previous literature (Darmouni 2020) and Figure I 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 the 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. Although 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 by using the whole pre-Lehman period to construct the weight. I take an average across loans within the firm and bank in measuring the weight.

Table S.18 shows the results. The first three columns show the results based on the credit supply shock that utilize the amount of loans, and the 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 the companies that face a negative credit supply shock decrease their output prices.

TABLE S.18: THE EFFECT OF THE CREDIT CRUNCH ON OUTPUT PRICE: VARIANT OF ΔL_f

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔlnP$_{fg}$: 2006q4-2007q2 to 2008q4-2009q2					
	(-ΔL_f): Amount of Loans			(-ΔL_f): Average Bank Share		
	OLS		IV	OLS		IV
			Lehman			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
$E[\Delta\text{lnP}]$	11.4	11.4	11.4	11.5	11.5	11.5
$E[\Delta\text{lnP}$:(-ΔL_{p90})-(-ΔL_{p10})$]$	-11.3	-47	-49.5	-15	-40	-97.5
Observations	1658	1658	1658	1417	1417	1417

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, the regression is weighted by initial sales, the 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 the post-Lehman FE, spread, maturity, and lagged ΔlnP$_{fg}$, and average bank share is the average bank share in the pre-Lehman period.

S6.G Different Price Indexes

In my main regression analysis, I follow Hottman, Redding, and Weinstein (2016) and utilize the nested CES demand system to construct the 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 VI 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 the dependent variable. Correspondingly, the negative credit supply shock (-ΔL_f) is measured in the period from 2006q4-2007q2 and 2007q4-2008q2 to 2008q4-2009q2. Table S.19 shows the results. Regardless of which index is used in the regression analysis, I still find that the companies that face a negative credit supply shock decrease their output prices. Although the first-stage F-statistics are smaller than 10 for some results, using the instrument directly as a measure of the credit supply shock does not change the result.

S6.H Listed vs. Unlisted Firms

I re-run my regression analysis reported in Table IV by restricting the sample to the firms that are present in the Compustat data. As shown in the first two columns of Table S.20, I find that the effect of a negative credit supply shock on output price is negative by using only listed firms. Similarly, using only unlisted firms generates similar results.

This analysis confirms that the results are not sensitive to using different subsample of firms. In particular, listed firms are likely to be included in the sample used in Gilchrist et al. (2017). This analysis

TABLE S.19: THE EFFECT OF THE CREDIT CRUNCH ON OUTPUT PRICE: DIFFERENT PRICE INDEXES

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \ln P_{fg}$: 2007q4-2008q2 to 2008q4-2009q2					
price index	Laspeyres		Paasche		Tornqvist	
	OLS	IV Lehman	OLS	IV Lehman	OLS	IV Lehman
$(-\Delta L_f)$	-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
$E[\Delta \ln P]$	3.18	3.18	2.6	2.6	1.52	1.52
$E[\Delta \ln P$:$(-\Delta L_{p90})$-$(-\Delta L_{p10})]$	-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.

TABLE S.20: THE EFFECT OF THE CREDIT CRUNCH ON OUTPUT PRICE: LISTED VS. UNLISTED FIRMS

	(1)	(2)	(3)	(4)
	$\Delta \ln P_{fg}$: 2007q4-2008q2 to 2008q4-2009q2			
	Listed Firms		Unlisted Firms	
ΔL_f	-2.34***	-9.98***	-2.59*	-7.26**
	(0.60)	(3.73)	(1.35)	(3.11)
Firm-level controls	No	Yes	No	Yes
Product group FE	No	Yes	No	Yes
Naics 4-digit FE	No	Yes	No	Yes
$E[\Delta \ln P]$	11.4	11.4	11.4	11.4
$E[\Delta \ln P$:ΔL_{p90}-$\Delta L_{p10}]$	-5.1	-21.8	-5.6	-15.8
Observations	739	735	919	914

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

further suggests that the difference in the results relative to previous studies does not arise from the difference in the sample, as discussed extensively in Section V.

S6.I Testing the Selection of Unobserved Variables

In this section, I additionally support my identification assumption by conducting a test that 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. Consider the following regression analysis:

$$\Delta \ln(\text{Loans}_{fb}) = \lambda_f + \gamma \Delta(\text{Bank Health})_{\text{-}f,b} + \varepsilon_{fb} \tag{56}$$

where f is firm, b is bank, Loans_{fb} is the amount of loans received by firm f from bank b, $\Delta(\text{Bank Health})_{\text{-}f,b}$ is the leave-one-out change in bank health that I measured in Section II.B, 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 the 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 the concern that arises from the fact that different firms might demand credit differently. However, excluding the firm fixed effect implies that I use variation across firms in estimating the γ coefficient. In this case, if it is true that different firms demand credit differentially, then the coefficient would be biased and different from the estimates with the firm fixed effect.

TABLE S.21: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by borrower and lender, the 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 the post-Lehman FE, spread, and maturity.

Table S.21 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 approximately 10 percent. This result suggests that the unobserved characteristics of firms are not likely to correlate with the credit supply shock measure that I constructed conditioned on observed characteristics.

S6.J Pre-trend Regression

I confirm the empirical results by checking the pre-trend with the same regression specification and credit supply shock as the equation (6) 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 the 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 the firms that faced negative credit supply shocks changed their output prices before the shock occurred. As shown in Table S.22, 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 II, where I plot the aggregate price indexes for two groups of firm—with one group facing a larger negative credit supply shock than the other group—based on the main measure constructed in equation (1). 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.

TABLE S.22: PRETREATMENT TRENDS REGRESSION

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \ln P_{fg}$: 2004q4-2005q2 to 2006q4-2007q2					
	OLS		$(-\Delta L_f)$ instrumented using			
			Lehman	ABX	BankItem	All
$(-\Delta L_f)$	-0.32	-0.57	1.35	-7.94	-2.96	-2.28
	(1.10)	(1.44)	(3.33)	(6.51)	(3.65)	(3.04)
firm-level controls	No	Yes	Yes	Yes	Yes	Yes
product group FE	No	Yes	Yes	Yes	Yes	Yes
naics 4-digit FE	No	Yes	Yes	Yes	Yes	Yes
First-stage F statistics			10.60	4.30	10.10	6.00
J-statstics p-value						0.21
$E[\Delta \ln P]$	4.9	4.9	4.9	4.9	4.9	4.9
$E[\Delta \ln P{:}\Delta L_{p90}\text{-}\Delta L_{p10}]$	-.71	-1.3	3.0	-17.6	-6.6	-5.1
Observations	1658	1658	1658	1658	1658	1658

Note * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors are clustered by firm and product group; the regression is weighted by initial sales; and firm-level controls are the firm's listed status, four-digit NAICS FE, age, 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

S6.K 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 although 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.[13] 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 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 the 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 the 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 that borrow from financial intermediaries, and the 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:

$$\Delta \ln P_{jt} = \lambda_j + \lambda_t + \delta(\mathrm{RZ}_j \times \Delta ff_t) + \theta X_{jt} + \varepsilon_{jt} \tag{57}$$

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, and λ_j and λ_t are industry and time fixed effects, respectively. X_{jt} represents industry-month-level control variables, including (NAICS 2-digit Dummies)$_j \times \Delta ff_t$, (Durability Index)$_j \times \Delta ff_t$, (Luxuriousness Index)$_j \times \Delta ff_t$, and $\mathrm{RZ}_j \times$(Month Dummies)$_t$. The Luxuriousness Index and Durability Index come from Bils, Klenow, and Malin (2013) and measure product luxuriousness and durability for each industry, respectively. The δ coefficient measures how the effect of the monetary policy shock on the

13. For example, Stroebel and Vavra (2019) 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 VI.

industry-level output price index dependent on external finance of the industry.

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 S.23. These results help ensure that the 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 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 is 0 otherwise. Then, I interact this variable with the shock variables, but I find no evidence that the effect is larger for the recession. Additionally, the results are robust when this recession period is excluded from the sample, which suggests 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, which is consistent with the fire sale of inventory hypothesis.

TABLE S.23: THE EFFECT OF THE CREDIT CRUNCH ON THE OUTPUT PRICE: EXTERNAL VALIDITY

	(1)	(2)	(3)	(4)
		$\Delta \ln P_{jt}$		
$\text{RZ}_j \times \Delta ff_t$	-0.172**	-0.166**	-0.155*	-0.173**
	(0.075)	(0.079)	(0.079)	(0.076)
$\text{D}_{\text{recession}} \times \text{RZ}_j$			-0.000	
			(0.000)	
$\text{D}_{\text{recession}} \times \text{RZ}_j \times \Delta ff_t$			-0.269	
			(0.253)	
$\text{RZ}_j \times \Delta ff_t$				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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by month and corrected for the autocorrelation by following Driscoll and Kray (1998), and the control variables are (NAICS 2-digit)$\times \Delta ff_t$, (Durability)$\times \Delta ff_t$, (Luxuriousness Index)$\times \Delta ff_t$, and $\text{RZ}_j \times$(Month Dummies)$_t$.

In addition, I divide all the recessions that occurred 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 plot the results in Figure S.7. As shown in the figure, inflation seems to fall in banking crises but rise in nonbanking crises, despite a large decrease in real GDP, which is consistent with the empirical findings in this article. This result is robust when I look

FIGURE S.7: 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 this 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).

only at the United States. Note that the magnitude of change in inflation in banking crises is quite different from the magnitude of change in inflation for nonbanking crises, as the data had more historical information for banking crises, when the average inflation was lower than in recent periods. Dropping the recession years before 1950 generates a similar magnitude of average inflation to the magnitude of average inflation in nonbanking crises, from 5 to 8 percent.

S7 LIQUIDITY POSITION

This section replicates Tables VII and VIII with slightly different specifications to corroborate the empirical evidence presented in Section V.

Table S.24 replicates the results in Gilchrist et al. (2017) by using both the lagged (2006) and contemporaneous (2008) liquidity. To show the robustness of the replication results, I do not allow regression weights in this specification, similar to Gilchrist et al. (2017). Columns (1) and (2) report the results by using the lagged (2006) liquidity, and columns (3) and (4) report the results by using the current (2008) liquidity. A coefficient of liquidity is negative and statistically significant in all four different specifications. In addition to the estimated effect reported in columns (1) and (2) of Table VII, these results confirm that the key difference in this article relative to the previous study is the measure of financial constraint, not the sample or regression specification.

TABLE S.24: THE EFFECT OF CORPORATE LIQUIDITY ON OUTPUT PRICE

	(1)	(2)	(3)	(4)
	$\Delta \ln P_{fg}$: 2006q4-2007q2 to 2008q4-2009q2			
	The Year of LIQ_f is			
	2006		2008	
LIQ_f	-5.24**	-4.84**	-6.76***	-7.01***
	(2.44)	(1.99)	(2.45)	(2.10)
Firm-level Controls	No	Yes	No	Yes
Observations	985	985	975	975

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, LIQ_f is the cash to assets, which is normalized to have a unit variance, and the firm-level controls are the 2006 inventory to sales, the 2004-2006 change in market share at the firm-group-level, and the 2004-2006 change in the number of employees. Across all specifications, the quality-adjusted utility-based price index is used and the lagged dependent variable is included, similar to Gilchrist et al. (2017), who use the quality-adjusted price index and control the lagged industry-level inflation.

Table S.25 presents the regression results by re-estimating equation (6) with the initial liquidity position. 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 columns (1) and (4), it seems that both bank shock and the initial liquidity position independently explain output price dynamics. After adding other firm-level control variables, however, the coefficient of the credit supply shock becomes larger and remains statistically significant as in Table IV, whereas the coefficient of the initial liquidity position changes sign and becomes statistically non-significant as in Table VII columns (3) and (4). These results support the view that the initial liquidity is highly correlated with the other characteristics of firms and cannot precisely measure the financial constraint.

Lastly, I revisit the analysis in Table VIII by replacing the 2008 firm-level characteristics with the 2006 firm-level characteristics. I regress the 2008 firm-level characteristics on 2006 liquidity to see how the firms that had high initial liquidity reacted during the financial panic of 2008. There are two polar opposite predictions of this regression analysis. First, given that the corporate cash holding is randomly allocated, the firms that have a large amount of cash before the financial panic were likely to hedge the financial shock in the middle of financial panic. In this case, such firms would be financially unconstrained and perform better in 2008. Second, given that the cash holding is endogenous to risk, the firms that hold more cash before the financial panic because they were risky in the beginning are thus more constrained in the middle of financial panic. In this case, such firms would be financially constrained and perform poorly relative to their counterparts in 2008.

As shown in Table S.26, empirical evidence suggests the latter prediction that the firms that have a large

TABLE S.25: THE EFFECT OF THE CREDIT CRUNCH ON OUTPUT PRICE: INCLUDING THE INITIAL LIQUIDITY

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \ln P_{fg}$: 2006q4-2007q2 to 2008q4-2009q2					
	OLS		IV ($-\Delta L_f$)	OLS		IV ($-\Delta L_f$)
			All			All
$(-\Delta L_f)$	-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
$E[\Delta \ln P]$	11.53	11.53	11.53	11.53	11.53	11.53
$E[\Delta \ln P$:$(-\Delta L_{p90})$-$(-\Delta L_{p10})]$	-4.78	-9.61	-12.35	-4.68	-8.72	-12.17
Observations	1318	1318	1318	1318	1318	1318

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, the regression is weighted by initial sales, and the 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 the post-Lehman FE, spread, maturity, and lagged $\Delta \ln P_{fg}$

TABLE S.26: 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	0.25***	-0.04***	-0.01**	-0.32***
	(0.03)	(0.01)	(0.00)	(0.05)
2-digit sic FE	No	No	No	No
R^2	0.12	0.02	0.00	0.12
obs	2638	3062	2962	2920
	cash flow volatility	capex to assets	acquisition to assets	debt to assets
cash to assets	0.21***	-0.02**	-0.01***	-0.28***
	(0.04)	(0.01)	(0.00)	(0.04)
2-digit sic FE	Yes	Yes	Yes	Yes
R^2	0.17	0.30	0.04	0.22
obs	2635	3059	2959	2917

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by the 2-digit SIC industry code. The 2006 cash to assets is used as an independent variable.

amount of cash underperform in the middle of financial panic. I find that the firms that had a large amount of liquidity in 2006 had an unstable cash flow, invested less, borrowed less, and spent less money to acquire other firms in 2008 compared to the firms that had a small amount of liquidity in 2006.[14] These results are true regardless of whether I allow the 2-digit SIC fixed effects. The empirical results imply that the firms that have more cash in 2006 were financially constrained to begin with and were constrained in 2008.

One caveat in interpreting the results in Table S.26 is that the 2006 initial cash holding is highly correlated with many other factors, as shown in Table VIII and Bates, Kahle, and Stulz (2009) and cannot be used as a single independent variable to make a concrete statement about 2008. For example, columns (3) and (4) of Table VII show that controlling other measures of financial constraint can completely change the effect of the initial cash holdings on the output price. Depending on the regression specifications, in principle, the effect of initial cash holdings on the outcome variables could change if the correlated factors affect the outcome variable. Table S.26 should be interpreted as suggestive evidence that corroborates the findings in Table VIII rather than a concrete statement.

S8 Calibration: Regression with a Dummy Variable

In this section, I show the regression results that I used to calibrate the magnitude of the shock parameter. I cannot directly use my estimated coefficient in Table IV, 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 is 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 (6)) by replacing the credit supply shock measure with the dummy variable above:

$$\Delta \ln P_{fg} = \lambda_g + \beta D_f + \theta X_f + \varepsilon_{fg} \tag{58}$$

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 S.27 shows the results. The estimated coefficient is approximately -15%. Accordingly, I calibrate the magnitude of the credit supply shock to the representative entrepreneur 1 so that the decrease in relative price is 15%.

14. The results are robust to using the average of firm characteristics in the period of 2008-09.

TABLE S.27: MAIN RESULT WITH DUMMY VARIABLE

	(1)	(2)	(3)
	ΔlnP$_{\text{fg}}$: 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
$E[\Delta\text{lnP}]$	11.4	11.4	11.4
Observations	1658	1658	1658

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the standard errors are clustered by firm and product group, the regression is weighted by initial sales, and the firm-level controls are 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 the post-Lehman FE, spread, maturity, and lagged ΔlnP$_{\text{fg}}$

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