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INFLATION DYNAMICS DURING THE FINANCIAL CRISIS

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ABSTRACT

Using a novel dataset, which merges good-level prices underlying the PPI with the respondents' balance sheets, we show that liquidity constrained firms increased prices in 2008, while their unconstrained counterparts cut prices. We develop a model in which firms face financial frictions while setting prices in customer markets. Financial distortions create an incentive for firms to raise prices in response to adverse financial or demand shocks. This reaction reflects the firms' decisions to preserve internal liquidity and avoid accessing external finance, factors that strengthen the countercyclical behavior of markups and attenuate the response of inflation to fluctuations in output.

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1 Introduction

In spite of substantial and persistent economic slack, the United States experienced only a mild disinflation during the "Great Recession" and its aftermath. Consumer price inflation, measured by the core PCE price index, averaged 2 percent between 2003 and 2007 and only declined to an average annual rate of about 1.5 percent over the following eight years, a period that saw the deepest contraction in economic activity since the Great Depression, followed by an uneven and weak recovery. Among many economists, the absence of more pronounced deflationary pressures during this period has cast doubt on the empirical relevance of the Phillips curve—a central tenet of most standard macroeconomic models—which posits that a high level of resource underutilization should cause inflation to fall over time (Hall, 2011; King and Watson, 2012).

The puzzling behavior of inflation during the Great Recession—at both the consumer and producer levels—has led to a vigorous research effort aimed at reconciling the observed inflation dynamics with the canonical Phillips curve-type relationships linking the rate of change in prices to the level of economic activity.[1] Importantly, the absence of significant deflationary pressures occurred against the backdrop of extraordinary turmoil that swept through financial markets in 2008, which resulted in a severe tightening of financial conditions for most businesses and households. To better understand the interaction between the firms' price-setting behavior and financial factors in periods of such turmoil, we analyze—both empirically and theoretically—inflation dynamics during the recent financial crisis through the lens of customer markets theory, while dispensing with the assumption of frictionless financial markets.

Our analysis intersects with three strands of the existing literature. First, the seminal contributions of Phelps and Winter (1970) and Bils (1989) show that pricing decisions in customer markets—markets in which a customer base is "sticky" and thus an important determinant of firms' assets and profitability—are a form of investment decisions because lower prices build the future customer base.[2] Second, recent work by Hottman et al. (2014) and Foster et al. (2016) documents that customer markets feature importantly in the major sectors of the U.S. economy. And lastly, as emphasized by Gottfries (1991) and Chevalier and Scharfstein (1996), in the presence of financial frictions, firms operating in customer markets that are experiencing a liquidity squeeze accompanying a fall in demand may find it optimal to maintain—or even increase—their prices and sacrifice future sales in order to boost current cashflows.[3]

[1] These explanations typically involve the "anchored expectations" hypothesis or alternative measures of economic slack (see Ball and Mazumder, 2011; Gordon, 2013; Krueger et al., 2014; Coibion and Gorodnichenko, 2015, and references therein). At the same time, Del Negro et al. (2015) argue that a standard New Keynesian model augmented with the financial accelerator mechanism of Bernanke et al. (1999) can match the broad contours of inflation during the crisis, without relying on large exogenous markup shocks; their results, however, rely heavily on the estimated degree of price stickiness, which is notably higher than that implied by the microeconometric evidence of Bils and Klenow (2004) and Nakamura and Steinsson (2008).

[2] The stickiness of the customer base may reflect a variety of microeconomic mechanisms: costly switching Klemperer (1987); costly search Hall (2008); or idiosyncratic preferences Bronnenberg et al. (2012).

[3] Some early empirical evidence supporting this hypothesis can be found in the work of Chevalier and Scharfstein (1996), Asplund et al. (2005), and Lundin et al. (2009). More recently, Antoun de Almedia (2015) and Gilchrist and Zakrajšek (2016) document a systematic effect of financial constraints on the industry-level producer prices in the euro area and United States, respectively. Using Spanish firm-level data, Montero and Urtasun (2014)

We first demonstrate the empirical relevance of this phenomenon for the Great Recession by constructing a new dataset, which merges *good-level* transaction prices underlying the U.S. Producer Price Index (PPI) with the respondent firms' income and balance sheet data from the Standard and Poor's Compustat. The key finding that emerges from our empirical analysis is that firms with limited internal liquidity and high operating leverage—a category of firms most exposed to liquidity shocks—significantly increased their prices in 2008, a period characterized by the widespread disruptions in credit markets and a sharp contraction in output. Their liquidity unconstrained counterparts, by contrast, cut prices during this period, a move consistent with the standard pricing models and the New Keynesian paradigm.[4]

To rationalize the fact that firms' balance sheet positions influenced their pricing behavior during the financial crisis, we incorporate the theoretical insights of Chevalier and Scharfstein (1996) into a tractable general equilibrium model, in which monopolistically competitive firms face costly price adjustment, while setting prices to actively manage current versus future expected demand. We do so in the context of the "deep habits" framework formulated by Ravn et al. (2006), which we augment with a financial distortion, namely, costly external equity finance. As in Gourio and Rudanko (2014), the firm's customer base in our model is an asset, and the presence of financial market frictions affects the incentive of firms to invest into such an asset via price reductions.

Relative to a setup with frictionless financial markets, our model implies a significantly different response of prices to adverse demand and financial shocks. The key mechanism driving this result is the interaction of financial frictions with customer markets. Faced with a sticky customer base and costly external finance, firms are confronted with a tradeoff between current profits and the longer-run consideration of their market share. Maintaining a market share requires a firm to post low prices. However, a firm can be forced to deviate from this strategy if an adverse shock induces a severe deterioration in its internal liquidity position. In that case, a firm will find it optimal to raise prices—and sacrifice its market share—to avoid costly external financing. Thus, pricing behavior becomes more myopic as financial constraints become more severe.

Extending our theoretical framework to allow for differences in financial conditions across firms, we further show that firms with weak balance sheets raise prices relative to firms with strong balance sheets in response to adverse demand or financial shocks. These theoretical results accord well with our empirical evidence, which shows that in 2008, firms with limited internal liquidity actually increased prices, while their financially stronger counterparts lowered prices. Because in our model firms with strong balance sheets are better positioned to reduce prices and "steal" market share from their financially constrained competitors, heterogeneity in financial conditions

employ an econometric framework to derive estimates of the price-cost margins and find a significant increase in the estimated margins during the 2007–2011 period; moreover, the increase in these implied markups was especially pronounced for firms facing tight credit conditions and for firms operating in industries with a low degree of product market competition. Using Japanese survey data, Kimura (2013) also finds evidence that the binding liquidity constraints among Japanese firms attenuated deflationary pressures arising from significant and persistent slack in the post-bubble Japanese economy of the 1990s.

[4] As shown in Appendix A, these differences in the price-setting behavior between liquidity constrained and unconstrained firms are also reflected in the differential behavior of employment, inventories, and other forms of investment, in a manner that is consistent with the presence of binding financial constraints.

leads to a further deterioration in the liquidity position of financially constrained firms. In addition to amplifying the overall contraction in output, such strategic pricing behavior is also in line with "limit pricing" strategy of Milgrom and Roberts (1982) and the theories of "predation based on agency problems" developed by Bolton and Scharfstein (1990).[5]

Financial market distortions also play a key role in the cyclical behavior of markups: In the model with financial frictions, markups remain elevated after the initial impact of an adverse demand (or financial) shock; in the case of frictionless financial markets, by contrast, the countercyclical dynamics of markups are significantly attenuated, as the initial increase in markups is offset by low future markups. Thus, the interaction of customer markets and financial frictions can account for the countercyclical nature of markups as well as for the stabilization of inflation at positive rates against the backdrop of significant and long-lasting economic slack.

Within the context of New Keynesian models, Christiano et al. (2015) also draw attention to the impact of financial frictions on inflation dynamics during the Great Recession. In their model, the jump in credit spreads in late 2008 induces a sharp rise in the cost of working capital, which increases firms' marginal costs—the "cost channel" documented by Barth and Ramey (2001). At the same time, the economy is hit by a series of exogenous negative technology shocks, which further boost firms' marginal costs. These two factors counteract the emergence of significant deflationary pressures and deliver only modest disinflation in the face of a significant contraction in output.

Although financial market frictions play a critical role in the work of Del Negro et al. (2015) and Christiano et al. (2015), neither of these papers seeks to account for the differences in the actual pricing behavior of firms in different financial positions during the Great Recession. And while the cost channel is also present in our model, it is not the primary mechanism through which financial frictions influence inflation dynamics during the crisis. Rather, our approach offers two distinct contributions to the understanding of inflation dynamics during a financial crisis. First, it provides new empirical evidence on how firms in different financial positions actually change their prices during a crisis. Second, it provides a link between these new micro facts and the macroeconomy by developing a tractable general equilibrium model, in which the strategic interaction of firms operating in customer markets and facing imperfect capital markets can in periods of widespread financial distress lead to economic outcomes characterized by a severe and persistent contraction in economic activity that is accompanied by only mild disinflation.

[5] In the standard financial accelerator model, by contrast, financial distortions reduce input demand but do not directly affect the firms' pricing decisions. In such environments, alleviating the severity of financial frictions for a subset of firms—which boosts the overall financial capacity of the economy and at the same time induces greater heterogeneity in financial conditions across firms—*reduces* the degree of amplification obtained through the financial accelerator.

2 Empirical Evidence

2.1 Data Sources and Methods

To document how firms' balance sheets affected their pricing behavior during the Great Recession, we construct a novel dataset using micro-level data from two sources: (1) *good-level* (confidential) producer price data underlying the PPI published by the Bureau of Labor Statistics (BLS); and (2) *firm-level* income and balance sheet data from Compustat. As emphasized by Nakamura and Steinsson (2008) and Goldberg and Hellerstein (2009), the good-level PPI data are transactions-based prices that are representative of the entire U.S. production sector and are consistently sampled, both across production units and time. Goods produced by each firm are uniquely identified, according to their "price-determining" characteristics such as the type of buyer, the type of market transaction, the method of shipment, the size and units of shipment, the freight type, and the day of the month of the transaction.

The granularity of these data allows us to overcome limitations inherent in working with macro-level price series because we can aggregate good-specific inflation rates to the firm level and thus preserve the cross-sectional heterogeneity of the firms' pricing decisions. In combination with the firm-level balance sheet data, we can then analyze directly how differences in financial conditions between firms translate into difference in their pricing behavior during the financial crisis. We focus on producer prices because they directly capture the price response of domestic production units to changes in the underlying economic and financial conditions.

We use the algorithm of Schoenle (2010) to match the names of firms in the PPI and Compustat datasets.[6] After applying the algorithm to the two datasets over the period from January 2005 to December 2012, we matched 584 U.S. nonfinancial corporations with the PPI database. To construct monthly inflation rates for these firms, we use *quality-adjusted* good-level prices, which control for potential changes in product quality over time. Specifically, letting $p^*_{i,j,t}$ denote the recorded transaction price of good i produced by firm j and $p^b_{i,j,t}$ the corresponding "base" price—which takes into account changes in the item's quality over time—we define the quality-adjusted good-level price as $p_{i,j,t} \equiv p^*_{i,j,t}/p^b_{i,j,t}$. The good-level inflation rate in month t—denoted by $\pi_{i,j,t}$—is then calculated as

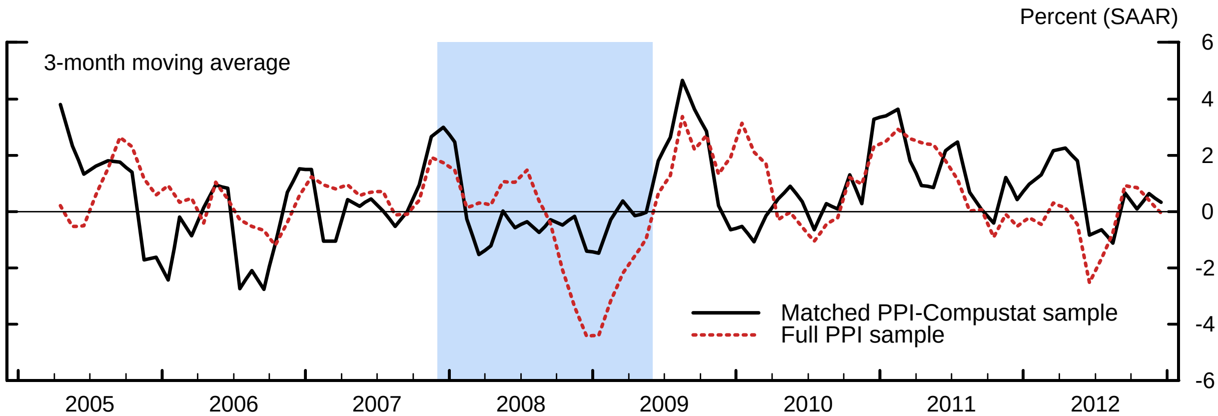
$$\pi_{i,j,t} = \Delta \log p_{i,j,t} = \Delta \log \left(\frac{p^*_{i,j,t}}{p^b_{i,j,t}} \right), \tag{1}$$

where $\Delta x_t \equiv x_t - x_{t-1}$.[7] We also use the quality-adjusted good-level prices to calculate other price-change characteristics, such as frequency of price changes, positive/negative price changes,

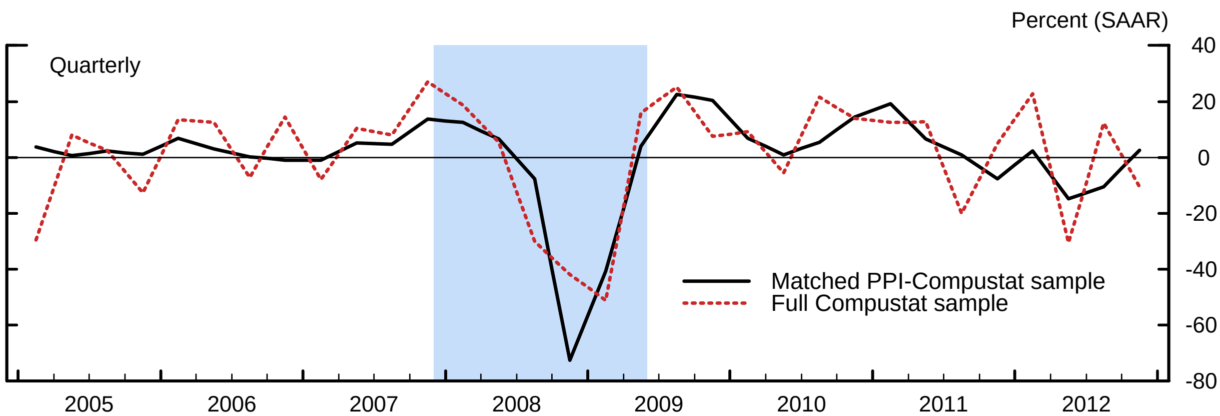
[6] Weber (2014) and Gorodnichenko and Weber (2016) also consider a matched sample of publicly traded firms to study asset pricing implications of nominal rigidities.

[7] To ensure the PPI measures only "pure" price changes—that is, changes attributable solely to market factors—it must exclude any change in price of the sampled items that is due to a change in the base price, such as physical changes to the item or changes in the way the item is sold. To adjust for such changes in the base price, the BLS employs a number of quality-adjustment procedures, which depend on the type of change and the information available from the respondent; see Bureau of Labor Statistics (2014) for details. To mitigate the effect of outliers on our results, we also exclude all observations with absolute monthly inflation rates in excess of 100 percent from our calculations.

Figure 1: Comparing Data with Broader Aggregates



(a) Producer price inflation



(b) Sales growth

Note: The solid line in panel (a) depicts the weighted-average of monthly good-level inflation rates for the sample of 584 firms in the matched PPI–Compustat sample, while the dotted line depicts the corresponding inflation rate calculated using the full PPI sample. The solid line in panel (b) depicts the quarterly weighted-average growth rate of sales for the sample of 584 firms in the matched PPI–Compustat sample, while the dotted line depicts the corresponding growth of sales calculated using the sample of all U.S. nonfinancial firms in Compustat; firm-level sales are deflated by the U.S. nonfarm business sector GDP price deflator (2009:Q4 = 100). The shaded vertical bar represents the 2007–2009 recession as dated by the NBER.

and frequency of positive/negative price changes.

Although the matched PPI–Compustat sample includes less than 600 firms, these firms tend to be appreciably larger than a typical U.S. nonfinancial corporation. As a result, the matched sample is representative of the U.S. economy as a whole in a number of dimensions relevant to our analysis.[8] Panel (a) of Figure 1 shows the weighted-average of good-level inflation rates calculated

[8] Table A-1 in Appendix A provides a comprehensive comparison of the pricing characteristics between the full PPI and matched PPI–Compustat datasets, while Table A-2 compares the key characteristics of firms in the matched PPI–Compustat sample with those of the entire U.S. nonfinancial corporate sector.

using the full PPI and the matched PPI–Compustat samples.[9] The average inflation rate based on the subset of publicly traded firms is somewhat noisier compared with the overall PPI inflation rate, but the two series are positively correlated and in broad terms capture the same cyclical behavior of producer prices. Panel (b) compares the weighted-average growth rate of sales for the matched PPI–Compustat sample with that of all nonfinancial firms in Compustat. The two series exhibit a high degree of comovement, especially during the Great Recession.

2.2 Inflation Dynamics by Selected Firm Characteristics

A defining feature of the recent financial crisis was a massive disruption in the credit intermediation process, both in the arm's-length capital markets and in the form of credit intermediated through the banking sector. With regards to the latter, Bassett et al. (2014) show that a significant portion of the decline in the capacity of businesses and households to borrow from the banking sector represented a reduction in the supply of credit lines, as banks aggressively reduced their off-balance-sheet credit exposures in response to the acute pressures on their capital and liquidity positions.

In 2008, with short-term funding markets in severe turmoil, this pullback in the supply of contingent liquidity that businesses rely upon heavily exerted a significant strain on corporate balance sheets, forcing companies to turn to internal sources of liquidity (Campello et al., 2011). As documented by Lins et al. (2010), bank credit lines are the primary source of liquidity for companies around the world, and firms use (non-operational) cash reserves as a buffer against cashflow shocks, especially during economic downturns. Given the special role of corporate cash holdings during the recent crisis, we use the ratio of cash and short-term investments to total assets (the liquidity ratio)—a measure of the firm's ability to turn short-term assets into cash to cover its immediate debt obligations and fund its operations—to analyze how differences in internal liquidity affected the firms' pricing behavior during this period.[10]

There is a growing recognition among economists that customer markets are a pervasive feature of the economic landscape. Recent work by Foster et al. (2016) shows that even within commodity-like product industries in the manufacturing sector, the endogenous "demand accumulation process," whereby the producer actively influences its future demand by making pricing decisions that build customer base at the expense of current profits, is a key factor explaining the small size and slow growth of new plants in such industries. At the retail level, Hottman et al. (2014) use scanner price and expenditure data on individual consumer products to show that demand differences—

[9] The weights used to aggregate the good-level inflation rates in each month t are the product of the relative weight of a good in the establishment's production structure and the relative weight of the establishment as measured by its total shipments. It is also worth noting that the more pronounced drop in producer prices during the latter patter of the Great Recession recorded in the full PPI dataset (see panel (a) of Figure 1) is due to the fact the matched PPI–Compustat sample omits a number of goods that experienced out-sized price declines during this period, reflecting the drop in the energy prices.

[10] Our focus on the firms' internal liquidity positions during the crisis is also motivated by the corporate finance literature, which emphasizes the role of agency problems and contractual frictions in financial markets as key determinants of cash holdings among firms. According to these theories, the accumulation of liquid assets is an insurance mechanism, whereby (risk-neutral) firms can overcome an inability to raise sufficient funds in capital markets when hit by a liquidity shock.

reflecting variation in quality and taste among consumers—are the principal reason why some firms succeed in the marketplace while others fail. In addition, as documented by Roberts et al. (2012), Eaton et al. (2015), and Fitzgerald et al. (2016), customer markets considerations also importantly shape the pricing decision of exporting firms in both advanced and emerging market economies.

In a recent paper, Gourio and Rudanko (2014) argue that a high level of sales and general administrative (SG&A) expenses may be indicative of whether a firm is operating in customer markets—the SG&A expenditures include advertising expenses and costs associated with maintaining a sales force, activities that are closely associated with developing and maintaining a loyal customer base. As emphasized by Gilchrist and Himmelberg (1998), however, significant SG&A spending can also signal high fixed costs of operation and hence high operating leverage. Falato et al. (2013), on the other hand, interpret a high level of SG&A expenditures as indicating that the firm relies heavily on intangible capital, which cannot be pledged as collateral in loan contracts. Note that the two latter interpretations have similar implications for the firms' pricing decisions in the presence of financial market frictions: Firms with high operating leverage or limited pledeable collateral face greater liquidity risk during economic downturns and have a natural incentive to increase prices when external financing is costly and internal liquidity is scarce. Indeed, as shown below, we use the operating-leverage interpretation of the SG&A expenditures to introduce differences in "financial capacity" across firms in our model.

To analyze how the strength of the firms' balance sheet interacted with their price-setting behavior during the crisis, we use the liquidity ratio to classify firms in the PPI–Compustat sample into "high" and "low" liquidity categories. Specifically, we sort firms into the two categories based on whether the firm's trailing 12-month moving average of the liquidity ratio in month $t-1$ is above or below the median of its distribution in that period, an approach that minimizes the switching of firms between the two categories due to seasonal or other temporary factors.[11] We also examine how the firms' price-setting behavior during the crisis differed among firms of varying degree of operating leverage. To do so, we calculate for each firm in our sample its average ratio of SG&A expenditures to sales (the SGAX ratio), using all the available data over the 2000–2004 period. Firms are then sorted into "high" and "low" SGAX categories based on whether their pre-sample average SGAX ratio is above or below the median of these firm-specific ratios; note that this classification scheme assigns a firm into one of the two SGAX categories over the entire 2005–2012 sample period.[12]

[11] The PPI data are monthly, whereas the Compustat data are quarterly but are recorded in months given by the firm's fiscal year. In merging the two data sets, we are thus able to preserve the monthly frequency of the PPI data.

[12] Both of our classification schemes result in an economically significant differences in their intended dimensions. According to Table A-3 in Appendix A, liquid assets account, on average, for only 3 percent of total assets in the low liquidity category, compared with an average of 21 percent in the high liquidity category. Similarly, over the 2005–2012 sample period, the average SGAX ratio in the low SGAX category is 0.13, compared with the average ratio of 0.37 in the high SGAX category.

2.2.1 Descriptive Analysis

Our first empirical exercise zeroes in on the differences in inflation dynamics between the different types of firms during the Great Recession. To take into account the industry-level cyclical price dynamics, we work with firm-specific *industry-adjusted* inflation rates—denoted by $\tilde{\pi}_{j,t}$—defined as

$$\tilde{\pi}_{j,t} = \sum_{i=1}^{N_{j,t}} w_{i,j,t} \times \left[\pi_{i,j,t} - \pi_t^{IND}\right],$$

where $\pi_{i,j,t}$ is the monthly inflation rate for good i produced by firm j (see equation 1), $N_{j,t}$ is the number of goods by firm j that are included in the PPI, $0 < w_{i,j,t} \leq 1$ is the relative weight of good i within the total shipments of firm j; and π_t^{IND} is the (quality-adjusted) average inflation rate in the 2-digit NAICS industry corresponding to good i.[13] For each category of firms, we then compute the weighted-average monthly inflation rate, with the weights equal to the nominal value of sales in month $t-1$, as recorded by Compustat.

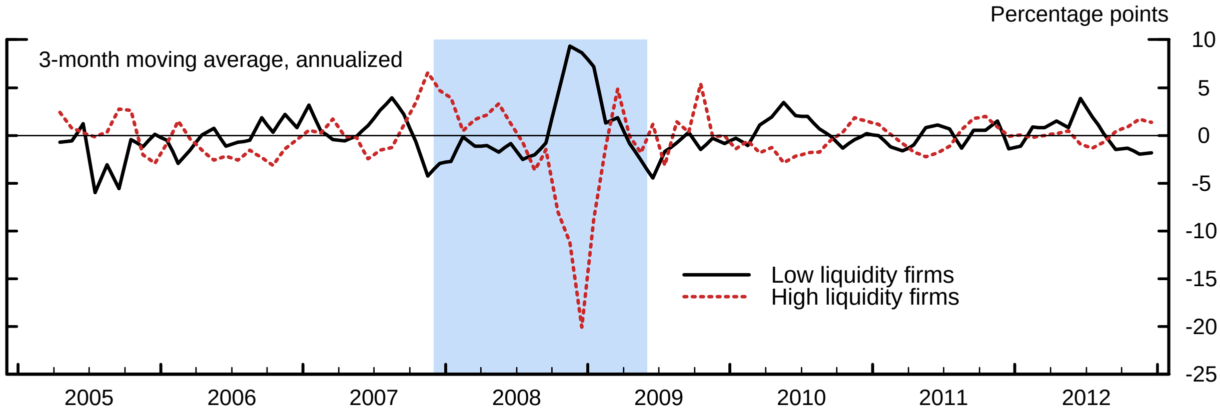
As shown in panel (a) of Figure 2, there is a sharp divergence in the behavior of industry-adjusted inflation rates between high and low liquidity firms in the latter part of 2008: Liquidity constrained firms significantly increased prices—relative to industry trends—whereas their unconstrained counterparts substantially lowered prices. The differences in the price-setting behavior between financially weak and strong firms are large in economic terms—by the end of 2008, the average inflation rate of liquidity constrained firms increased by more than 25 percentage points (annualized) relative to the inflation rate of liquidity unconstrained firms. Outside this period of acute financial turmoil, however, the inflation patterns between these two categories of firms do not exhibit any clear systematic differences.

These results are difficult to reconcile with the standard price-adjustment mechanism emphasized by the New Keynesian literature, a paradigm where firms' financial conditions play no role in determining their price-setting behavior. In the absence of large unobservable markup shocks, standard calibrations of these models imply a significant broad-based decline in producer prices in response to a contraction in output of the magnitude experienced by the U.S. economy in the latter part of 2008 (Hall, 2011; King and Watson, 2012). Moreover, if a low (pre-determined) liquidity ratio—which is used to measure the strength of the firms' balance sheets—was indicative of weakness in demand, one would expect liquidity constrained firms to lower prices even more relative to firms with ample internal liquidity. However, we observe exactly the opposite pattern in the data.

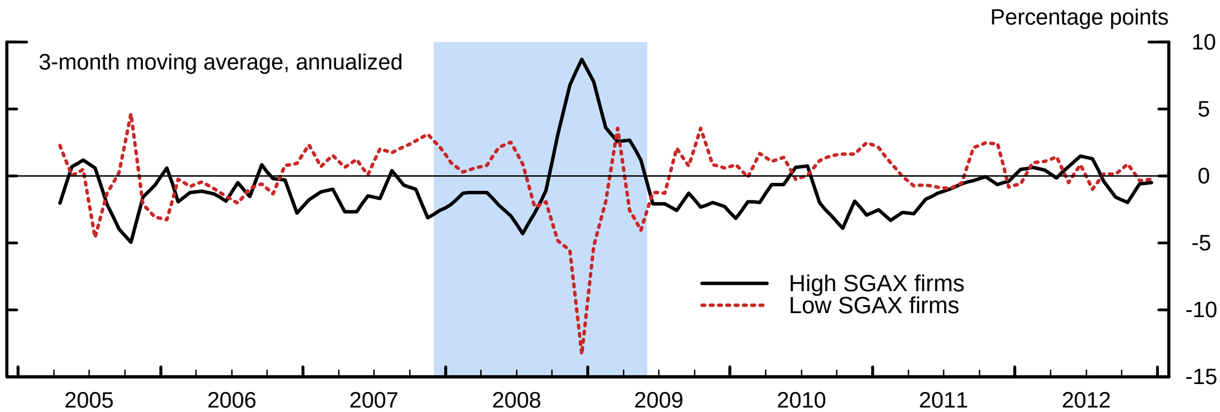
A similar divergence in industry-adjusted inflation rates emerges in panel (b) of Figure 2, where firms are sorted by the intensity of their (pre-sample) SG&A spending. High SGAX firms also

[13] Formally, $w_{i,j,t} = w^*_{i,j,t} \times \theta_{j,t}$, where $w^*_{i,j,t}$ denotes the relative weight of good i in the production structure of firm j (as recorded by the BLS), and $\theta_{j,t}$ is an adjustment factor that takes into account the fact that when merging the PPI database with Compustat more than one PPI respondent may fall within the definition of the Compustat firm j. To take into account this feature of the data, the adjustment factor equals the relative value of shipments of one PPI respondent with respect to all other respondents within the same Compustat firm unit. It is also important to note that the (2-digit NAICS) industry-specific inflation rates (π_t^{IND}) are constructed using the entire PPI database and not just the good-level price data corresponding to the matched PPI–Compustat sample.

Figure 2: Industry-Adjusted Producer Price Inflation
(*By Selected Firm Characteristics*)



(a) By liquidity ratio



(b) By SGAX ratio

Note: The solid (dotted) line in panel (a) depicts the weighted-average industry-adjusted inflation rate for low (high) liquidity firms. The solid (dotted) line in panel (b) depicts the weighted-average industry-adjusted inflation rate for high (low) SGAX firms. All underlying series are seasonally adjusted and annualized. The shaded vertical bar represents the 2007–2009 recession as dated by the NBER.

increased prices significantly during the nadir of the crisis—low SGAX firms, in contrast, lowered prices relative to industry trends during this period. While the price response of low SGAX firms is consistent with the standard competitive market price dynamics, the relative price increase of high SGAX firms appears to support the interpretation of SG&A expenditures as an indicator of customer markets—firms operating in such an environment and facing financial constraints will raise prices during a liquidity crunch at the expense of future market shares. As discussed above, to the extent that a substantial part of the firm's SG&A expenditures reflects overhead costs, a high SGAX ratio is indicative of high operating leverage. Facing both a liquidity squeeze and falling cashflows, high SGAX firms may thus be forced to boost prices in order to cover immediate debt obligations and help fund operations.

A potential concern with the results in panel (a) is that the difference in inflation rates between high and low liquidity firms during the crisis is due to firms moving from one category to another or firms altering their liquidity positions as the crisis unfolds. To rule out these possibilities, we consider an alternative sorting procedure, whereby companies are permanently assigned into high and low liquidity categories based on their average liquidity ratio in 2006—that is, before the onset of the financial crisis. Using this ex ante classification scheme, we also analyze the relative dynamics of *real* sales, a proxy for real output, between liquidity constrained and unconstrained firms.

Specifically, we construct the quarterly growth rate of real sales for firm j as

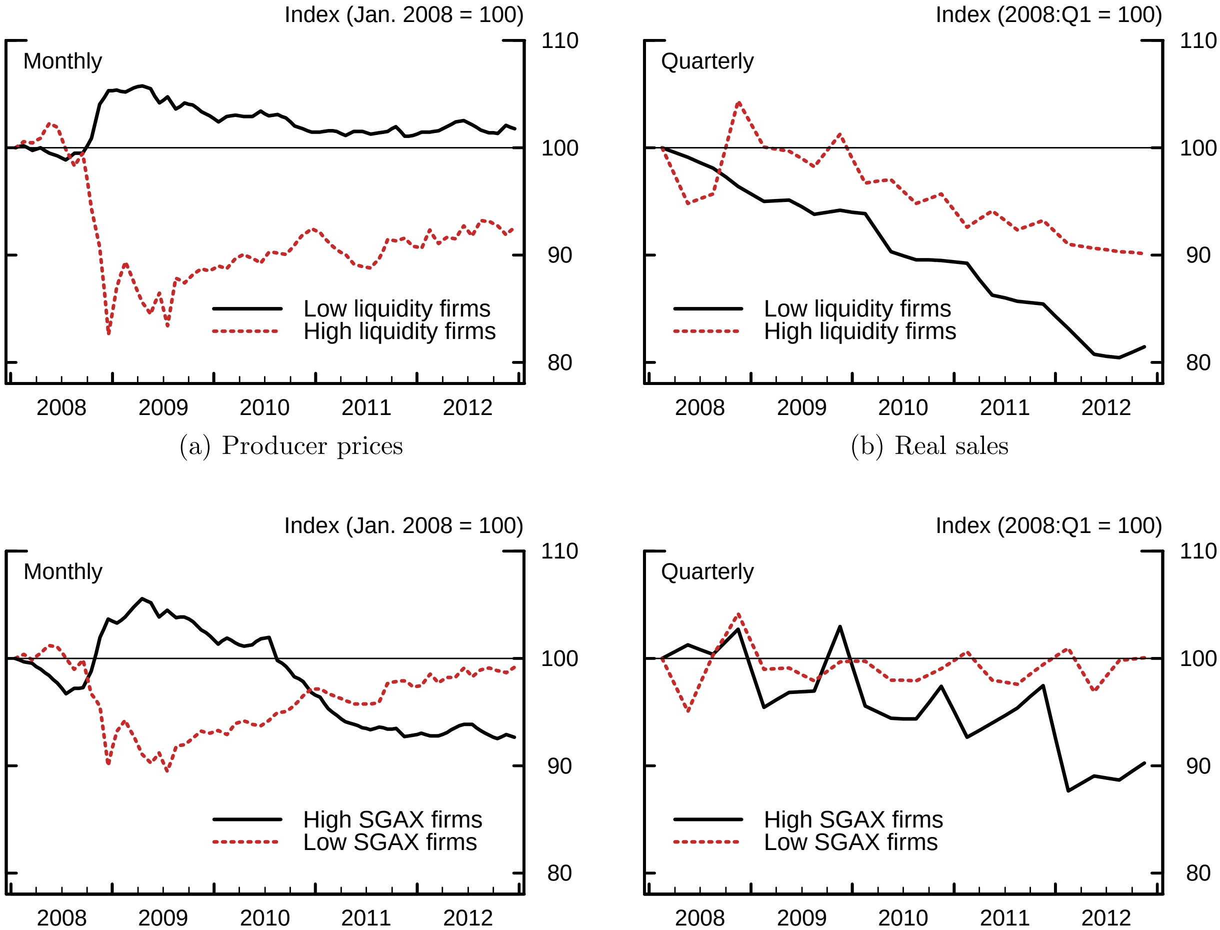
$$\Delta \log \tilde{S}_{j,t} = \Delta \log S_{j,t} - \sum_{i \in j} w_{i,j,t} \times \pi^{3m}_{i,j,t},$$

where $\Delta \log S_{j,t}$ is the quarterly log-difference of nominal sales as recorded by Compustat, and $\sum_{i \in j} w_{i,j,t} \times \pi^{3m}_{i,j,t}$ is the corresponding (3-month) weighted-average inflation rate of all goods produced by firm j calculated from the micro-level PPI data (see equation 1). We then sort firms into low and high liquidity categories based on their average liquidity ratio in 2006. To control for the differential effects of industry-specific shocks on output dynamics, we regress the growth of real sales in each sample of firms on the interaction of industry (3-digit NAICS) and time fixed effects and then calculate the cross-sectional (sales-weighted) average of the residuals in each quarter.

Panel (a) of Figure 3 shows the accumulated industry-adjusted inflation rates for the liquidity constrained and unconstrained firms based on our ex ante classification scheme. The sharp divergence in industry-adjusted inflation rates between financially strong and weak firms in the latter part of 2008 shown in panel (a) of Figure 2 is clearly evident in the case of this ex ante classification scheme, which abstracts from the compositional effects associated with firms switching between the two categories. Moreover, this divergence—although fairly short-lived—has significant long-term consequences for the behavior of relative prices for these two types of firms. The weighted average of prices charged by the ex ante liquidity constrained firms remains persistently above that charged by the firms that had more liquid balance sheets in 2006, even when taking into account the industry-level price dynamics.

The cyclical dynamics of real sales for the corresponding two categories of firms are shown in panel (b). The relative behavior of industry-adjusted real sales accords remarkably well with the divergence in industry-adjusted producer prices between liquidity constrained and unconstrained firms. As the evaporation of market liquidity disrupted the flow of credit to businesses and households in the second half of 2008, real sales of the ex ante liquidity unconstrained firms increased markedly relative to those of their financially weaker counterparts, a pattern consistent with the fact that the financially strong firms slashed prices during this period. Also consistent with the relative pricing trends shown in panel (a) is the fact that for the remainder of our sample period, industry-adjusted real sales of the ex ante liquidity constrained firms remained persistently below those registered by firms that had more liquid balance sheets prior to the crisis.

Figure 3: Industry-Adjusted Producer Prices and Sales
(*By Selected Firm Characteristics*)



(a) Producer prices (b) Real sales

(c) Producer prices (d) Real sales

Note: The solid (dotted) line in panel (a) depicts the cumulative weighted-average industry-adjusted inflation rates for low (high) liquidity firms, while the solid (dotted) line in panel (b) depicts the cumulative weighted-average industry-adjusted real sales growth for low (high) liquidity firms; firms are sorted into high and low liquidity categories based on their 2006 liquidity ratio. The solid (dotted) line in panel (c) depicts the cumulative weighted-average industry-adjusted inflation rates for high (low) SGAX firms, while the solid (dotted) line in panel (d) depicts the cumulative weighted-average industry-adjusted real sales growth for high (low) SGAX firms; firms are sorted into high and low SGAX categories based on their average pre-sample SGAX ratio.

Panels (c) and (d) of Figure 3 present the same information for firms with varying intensity of SG&A spending. According to panel (c), the divergence in industry-adjusted prices between the low and high SGAX firms during the nadir of the crisis is notably less pronounced; moreover, the difference dissipates within a couple of years. Consequently, as shown in panel (d), there is appreciably less divergence in industry-adjusted real sales between the low and high SGAX firms during this period.[14]

[14]Our analysis of the micro-level data also indicates that the deflationary pressures during the recent financial crisis

2.2.2 Multivariate Analysis

We now turn to regression analysis to examine formally how differences in the strength of firms' balance sheet affect their price-setting behavior. Specifically, we consider two pricing decision variables: (1) the firm's observed decision to change prices at the good level—a variable representing the extensive margin of price adjustment; and (2) good-level price inflation, which reflects the combined effect of the extensive and intensive margins of price adjustment. In the first case, we estimate a multinomial logit regression

$$\Pr\big(\operatorname{sgn}[p_{i,j,t+3} - p_{i,j,t}]\big) = \begin{cases} - \\ 0 \\ + \end{cases} = \Lambda(\boldsymbol{\beta}'\mathbf{X}_{j,t} + \gamma\pi_t^{IND(3m)}), \tag{2}$$

where $\operatorname{sgn}[p_{i,j,t+3} - p_{i,j,t}]$ is a discrete variable that equals "$-$" if the price of good i (produced by firm j) decreased between months t and $t+3$; "$+$" if the price of good i increased between months t and $t+3$; and "0" if the price of good i did not change during this 3-month period (the base category). In the second case, we estimate a linear pricing regression

$$\pi_{i,j,t+3}^{3m} = \boldsymbol{\beta}'\mathbf{X}_{j,t} + \gamma\pi_t^{IND(3m)} + u_{i,j,t+3}, \tag{3}$$

where $\pi_{i,j,t+3}^{3m} = \log p_{i,j,t+3} - \log p_{i,j,t}$ is the inflation rate of good i from month t to month $t+3$.

In both specifications, the good-level dependent variables are modeled as functions of firm-specific covariates $\mathbf{X}_{j,t}$ and $\pi_t^{IND(3m)}$, the (3-month) 3-digit NAICS producer price inflation corresponding to good i, which controls for the cyclical pricing dynamics at a narrowly defined industry level. The key firm-specific explanatory variable is the liquidity ratio in month t, denoted by $\mathrm{LIQ}_{j,t}$. To capture the differential effect of firms' internal liquidity positions on their pricing decisions during the financial crisis, we interact the liquidity ratio with the crisis indicator $\mathbf{1}[\mathrm{CRISIS}_t]$, which equals 1 between January and December 2008 and 0 otherwise. Additional firm-specific covariates are the 12-month log-difference of nominal sales and the cost of goods sold ($\log(S_{j,t}/S_{j,t-12})$ and $\log(C_{j,t}/C_{j,t-12})$, respectively) and the inventory-sales ratio in month t ($[N/S]_{j,t}$). The inclusion of the growth of sales and cost of goods sold controls for the cyclical changes in demand and direct costs attributable to the production of goods sold by the firm, while the inventory-sales ratio captures precautionary liquidity demand that may arise from the need to finance inventories during a downturn (Kashyap et al., 1994; Barth and Ramey, 2001).

Panel (a) of Table 1 summarizes the estimation results based on the full sample of firms: The two columns of the MLOGIT specification report the marginal effects of the specified explanatory variable on the probability of upward (+) and downward (−) price adjustment, relative to no price

were concentrated primarily in nondurable goods manufacturing (see Figure A-1 in Appendix A), a result consistent with the evidence in Bils et al. (2013). Moreover, relative price deflation within that sector appears to reflect solely a large price cut by liquidity unconstrained firms or firms with a low level of SG&A expenditures relative to sales. In contrast, nondurable goods manufacturers with weak balance sheets or those with a high SGAX ratio significantly increased—relative to industry trends—prices during the crisis.

Table 1: Liquidity and the Price-Setting Behavior of Firms During the Financial Crisis

Explanatory Variables	MLOGIT (+)	MLOGIT (−)	OLS (π^{3m})
(a) *Time-varying liquidity ratio*[a]			
$\text{LIQ}_{j,t} \times \mathbf{1}[\text{CRISIS}_t = 1]$	-0.433^{***}	-0.012	-0.029^{***}
	(0.107)	(0.072)	(0.009)
$\text{LIQ}_{j,t} \times \mathbf{1}[\text{CRISIS}_t = 0]$	-0.143^{**}	-0.044	-0.012^{***}
	(0.068)	(0.050)	(0.004)
$\log(S_{j,t}/S_{j,t-12})$	-0.020	-0.042^{*}	0.004
	(0.025)	(0.025)	(0.003)
$\log(C_{j,t}/C_{j,t-12})$	0.017	0.020^{*}	-0.002
	(0.013)	(0.011)	(0.002)
$[N/S]_{j,t}$	-0.022	-0.020	0.001
	(0.021)	(0.024)	(0.001)
$\pi_t^{IND(3m)}$	1.182^{***}	-0.127	0.134^{**}
	(0.333)	(0.170)	(0.055)
(b) *Pre-crisis liquidity ratio*[b]			
$\text{LIQ}_{j,2006} \times \mathbf{1}[\text{CRISIS}_t = 1]$	-0.394^{***}	-0.098	-0.021^{**}
	(0.083)	(0.076)	(0.008)
$\text{LIQ}_{j,2006} \times \mathbf{1}[\text{CRISIS}_t = 0]$	-0.245^{***}	-0.051	-0.017^{***}
	(0.080)	(0.054)	(0.004)
$\log(S_{j,t}/S_{j,t-12})$	-0.044	-0.029	0.004
	(0.033)	(0.027)	(0.005)
$\log(C_{j,t}/C_{j,t-12})$	0.047^{*}	0.019	-0.003
	(0.024)	(0.021)	(0.005)
$[N/S]_{j,t}$	-0.021	-0.013	0.000
	(0.020)	(0.023)	(0.001)
$\pi_t^{IND(3m)}$	1.052^{***}	-0.152	0.118^{**}
	(0.299)	(0.148)	(0.047)

Note: The dependent variable in the multinomial logit specification (MLOGIT) is $\text{sgn}[p_{i,j,t+3} - p_{i,j,t}]$, a discrete variable that equals "+" if the price of good i (produced by firm j) increased between months t and $t+3$; "−" if the price of good i decreased between months t and $t+3$; and "0" if the price of good i did not change during this 3-month period (the base category). The dependent variable in the linear regression specification (OLS) is $\pi^{3m}_{i,j,t+3} = \log p_{i,j,t+3} - \log p_{i,j,t}$, the inflation rate of good i from month t to month $t+3$. In addition to the specified explanatory variables, both specifications include time fixed effects. Asymptotic standard errors reported in parentheses are clustered at the firm level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] Sample period: 2005:M1 to 2012:12 at a quarterly frequency; No. of firms = 547; Obs. = 89,803.

[b] Sample period: 2007:M1 to 2012:12 at a quarterly frequency; No. of firms = 511; Obs. = 73,400.

change; specification OLS, in contrast, reports the corresponding effects for the overall inflation (π^{3m}). According to column (+), differences in internal corporate liquidity imply significant differences in the propensity of firms to increase their prices during the recent crisis: The point estimate of -0.433 associated with the interaction term $\text{LIQ}_{j,t} \times \mathbf{1}[\text{CRISIS}_t = 1]$ indicates that in 2008, a difference in the liquidity ratio of two standard deviations around the mean (32 percentage points according to Table A-2 in Appendix A) implies an almost 14 percentage point higher probability of a price *increase* for a low liquidity firm—relative to the baseline case of no price change—compared with its high liquidity counterpart.

In addition to being statistically highly significant, this effect is economically meaningful, as the unconditional probability of an upward price adjustment over a 3-month period is roughly 30 percent for both low and high liquidity firms (see Table A-3 in Appendix A). Thus in 2008, firms in a weak liquidity position were much more likely to raise their prices, compared with their financially stronger counterparts. Outside this period of extreme financial turmoil, differences in the firms' internal liquidity positions have, in economic terms, a significantly smaller effect on the likelihood of a price increase. Interestingly, variations in companies' cash stocks have no discernible effect on the propensity of firms to lower their prices (column $(-)$).

The results reported in column (π^{3m}) also comport with the notion that differences in the firms' internal liquidity positions significantly influenced producer price inflation during the crisis: A two standard deviation difference in the liquidity ratio across firms during the crisis period implies a difference in the annualized inflation of almost 4 percentage points over the subsequent three months. Outside the crisis period, by contrast, such a difference in the liquidity ratio across firms is associated with an inflation differential of only about 1.5 percentage points.

To obviate concerns about the possible endogeneity of the firms' liquidity positions as the crisis unfolds, panel (b) of Table 1 reports the results from estimating the pricing regressions (2) and (3) using the firms' pre-crisis liquidity ratio—that is, the proportion of liquid assets on the firms' balance sheet in 2006 ($\text{LIQ}_{j,2006}$), prior to any widespread concerns that the U.S. economy was heading towards a financial crisis. Reassuringly, these results are very similar—in both economic and statistical terms—to those in panel (a).[15] For example, as shown in column $(+)$, firms in a weak internal liquidity position in 2006 were much more likely to increase prices in 2008, compared with their ex ante financially stronger counterparts. Moreover, the pre-crisis differences in liquidity ratios among firms have no effect on the firms' propensity to lower prices, either in normal times or in periods of acute financial stress (column $(-)$). And as shown in column (π^{3m}), variations in the pre-crisis liquidity positions imply differential inflation outcomes of comparable magnitudes—during both normal and crisis times—to those estimated using a time-varying liquidity ratio.

Of course, the fact that the effects of internal liquidity on inflation dynamics during the crisis are virtually the same regardless of whether we condition on the pre-determined (time-varying) liquidity ratio or on the pre-crisis (time-invariant) ratio does not decisively establish that internal liquidity matters for the firms' pricing decision due to financial frictions. Cash holdings could affect the firms' price-setting behavior for reason unrelated to financial frictions. For example, firms operating in a standard competitive environment and facing highly cyclical demand may choose to accumulate more liquid assets in order to smooth dividends during the course of a business cycle, compared with firms in industries characterized by more stable demand. To the extent that our set of control variables does not fully capture such systematic cyclical differences in demand,

[15] In addition to the comparable magnitudes of the estimated coefficients associated with the firms' internal liquidity positions across the two panels, the standard deviation in the pre-crisis liquidity ratio is 14 percent a mere 2 percentage point less than the standard deviation of the liquidity ratio implied by the full sample.

our regressions would yield a similar result: Ample liquidity would predict a larger price decline during the crisis—this result, however, would reflect a standard price response in the face of a more pronounced fall in product demand.

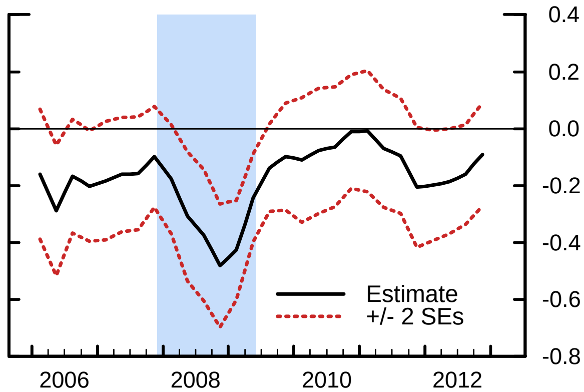
There are, however, several pieces of evidence that weigh strongly against this alternative hypothesis. First, the behavior of industry-adjusted real sales during the crisis (see panel (b) of Figure 3) shows that real sales at the ex ante liquidity flush firms actually increased compared with the real sales at the ex ante liquidity constrained firms. In addition, as shown in Table A-4 in Appendix A, employment and inventories became, conditional on sales, markedly more sensitive to internal liquidity during the crisis period. As argued by Bils and Kahn (2000), these results provide further evidence that markups of liquidity constrained firms become more countercyclical in periods of widespread turmoil in financial markets.

Another potential concern with the analysis reported in panel (a) is that we only allow the coefficient on the liquidity ratio to change during the crisis. It is plausible that the impact of other explanatory variables is also different in such extreme circumstances. To examine the sensitivity of our results to this assumption, we re-estimate specifications (2) and (3) using a rolling four-quarter window, thereby allowing for time-series variation in all the response coefficients. Panels (a) and (b) of Figure 4 show the estimated time-varying marginal effects of the liquidity ratio on the probability of a price increase and a price decrease, respectively. These results further corroborate our main finding that differences in corporate liquidity significantly affected the propensity of firms to increase prices in 2008. As shown in panel (a), the pronounced decline in the marginal effect during the crisis implies that firms with low levels of internal liquidity were much more likely to increase prices, compared with their liquidity unconstrained counterparts. Moreover, the estimate of this marginal effect on the probability of upward price adjustment is at the end of 2008 virtually the same as that reported in panel (a) of Table 1. Also consistent with our previous results is the fact that differences in the firms' internal liquidity positions have an insignificant effect on the propensity to lower prices throughout the sample period.

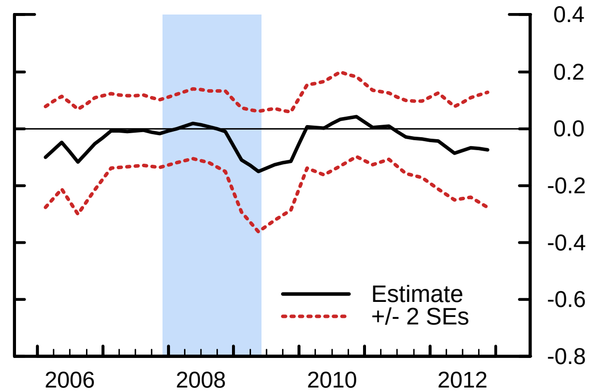
Panel (c) of Figure 4 depicts the time-varying effect of the liquidity ratio on the 3-month producer price inflation. As before, a low liquidity ratio during the crisis period foreshadows an economically and statistically significant increase in inflation over the subsequent three months. As in the case of the multinomial logit regression, the estimate of this effect at the end of 2008 is very close to that based on the full-sample specification reported in panel (a) of Table 1. Note also that a very similar effect of internal liquidity on the firms' price-setting behavior emerges in late 2011, when the vicious feedback loop between fiscal and financial-sector distress in the euro-zone periphery raised uncertainty among firms—not only in the euro area, but also in the United States—as to whether they would be able to access bank funding in the future.

Our last empirical exercise analyzes how differences in internal liquidity influence the pricing behavior of firms of varying intensity of SG&A spending. To do so, we split the sample of firms into low and high SGAX categories and estimate the pricing regressions (2) and (3) separately for each category. Focusing first on the high SGAX firms, panel (a) of Table 2, one can see

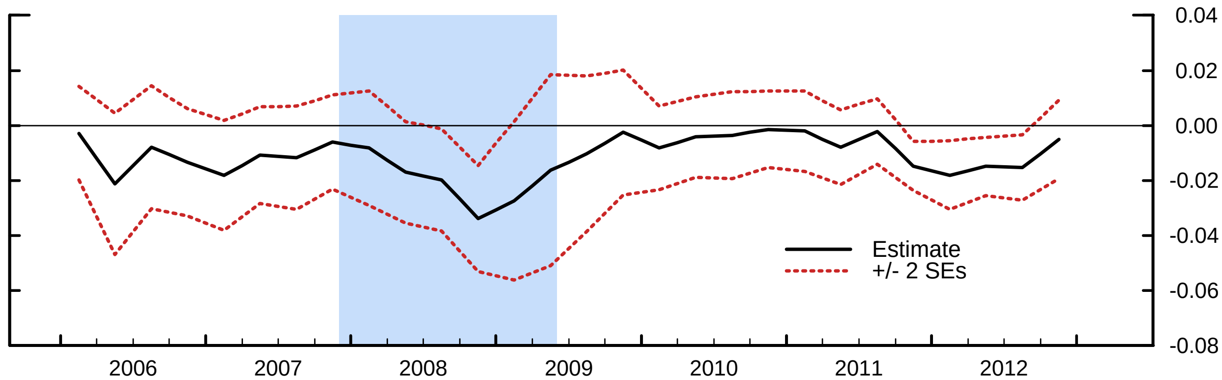
Figure 4: Time-Varying Effect of Liquidity on the Price-Setting Behavior of Firms



(a) Probability of a price increase



(b) Probability of a price decrease



(c) Producer price inflation

Note: The solid lines in panels (a) and (b) depict the time-varying estimates of the (average) marginal effect of the liquidity ratio on the probability of the 3-month-ahead positive and negative price changes (relative to no change), respectively. The solid line in panel (c) depicts the time-varying OLS estimate of the coefficient measuring the effect of liquidity ratio on the 3-month-ahead producer price inflation. The estimates are plotted at the end-point of the rolling four-quarter estimation window. Asymptotic standard errors are clustered at the firm level. The shaded vertical bar represents the 2007–2009 recession as dated by the NBER.

significant differences in how variations in their internal liquidity positions affect subsequent pricing decision. Within this category, a difference in the liquidity ratio of 32 percentage points during the crisis implies more than a 12 percentage points higher probability of a price increase for a low liquidity firm, compared with its high liquidity counterpart (column (+)). Outside the crisis, the likelihood that such a financially vulnerable firm will raise its prices over a 3-month period is about 5 percentage points higher than for a firm in a much stronger financial position. These differential internal liquidity effects are also evident in the inflation outcomes (column (π^{3m})): During the crisis, the same-sized variation in the liquidity ratio across high SGAX firms implies a differential in the annualized producer price inflation over the subsequent three months of about 6 percentage points.

Table 2: High SGAX vs. Low SGAX Firms

Explanatory Variables	MLOGIT (+)	MLOGIT (−)	OLS (π^{3m})
(a) *High SGAX Firms*			
$\text{LIQ}_{j,t} \times \mathbf{1}[\text{CRISIS}_t = 1]$	−0.386***	−0.061	−0.013**
	(0.125)	(0.072)	(0.006)
$\text{LIQ}_{j,t} \times \mathbf{1}[\text{CRISIS}_t = 0]$	−0.159***	−0.043	−0.006*
	(0.062)	(0.051)	(0.004)
$\log(S_{j,t}/S_{j,t-12})$	−0.004	−0.052**	0.008
	(0.025)	(0.026)	(0.005)
$\log(C_{j,t}/C_{j,t-12})$	0.011	0.032*	−0.005
	(0.016)	(0.018)	(0.004)
$[N/S]_{j,t}$	−0.024	−0.025	0.002
	(0.020)	(0.024)	(0.002)
$\pi_t^{IND(3m)}$	1.114***	−0.587*	0.216***
	(0.243)	(0.306)	(0.062)
(b) *Low SGAX Firms*			
$\text{LIQ}_{j,t} \times \mathbf{1}[\text{CRISIS}_t = 1]$	−0.211	0.331**	−0.062**
	(0.207)	(0.153)	(0.024)
$\text{LIQ}_{j,t} \times \mathbf{1}[\text{CRISIS}_t = 0]$	0.185	0.116	−0.001
	(0.149)	(0.119)	(0.006)
$\log(S_{j,t}/S_{j,t-12})$	−0.027	−0.025	0.001
	(0.039)	(0.038)	(0.004)
$\log(C_{j,t}/C_{j,t-12})$	0.026	0.013	0.001
	(0.019)	(0.014)	(0.003)
$[N/S]_{j,t}$	−0.019	−0.004	−0.001
	(0.035)	(0.036)	(0.002)
$\pi_t^{IND(3m)}$	0.894*	−0.001	0.080
	(0.472)	(0.186)	(0.058)

Note: Sample period: 2005:M1 to 2012:12 at a quarterly frequency. Panel (a): No. of firms = 258; Obs. = 33,279. Panel (b): No. of firms = 269; Obs. = 55,049. The dependent variable in the multinomial logit specification (MLOGIT) is $\text{sgn}[p_{i,j,t+3} - p_{i,j,t}]$, a discrete variable that equals "+" if the price of good i (produced by firm j) increased between months t and $t+3$; "−" if the price of good i decreased between months t and $t+3$; and "0" if the price of good i did not change during this 3-month period (the base category). The dependent variable in the linear regression specification (OLS) is $\pi^{3m}_{i,j,t+3} = \log p_{i,j,t+3} - \log p_{i,j,t}$, the inflation rate of good i from month t to month $t+3$. In addition to the specified explanatory variables, both specifications include time fixed effects. Asymptotic standard errors reported in parentheses are clustered at the firm level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

In contrast, as shown in panel (b), differences in internal liquidity positions among low SGAX firms have no differential effect on the propensity of these firms to *raise* prices (column (+)). The liquidity of their balance sheets, however, does affect the likelihood of low SGAX firms to *lower* prices, though only during the financial crisis (column (−)). In that case, a firm flush with internal liquidity is significantly more likely—in both economic and statistical terms—to lower prices, compared with a liquidity constrained firm. This result is consistent with the interpretation of a low SGAX ratio as an indicator of low operating leverage, which lessens the exposure of such firms to liquidity risk in periods of widespread financial distress. As a result, low SGAX firms with ample internal liquidity are able to cut their prices aggressively in periods of falling demand and tight credit, a finding consistent with the economically and statistically significant negative estimate of the coefficient on liquidity ratio during the financial crisis ($\text{LIQ}_{j,t} \times \mathbf{1}[\text{CRISIS}_t = 1]$) reported in column ($\pi^{3m}$).

In sum, our empirical analysis strongly supports the notion that internal liquidity positions played an important role in shaping the firms' price-setting behavior during the Great Recession. The drying up of external liquidity such as commercial paper and bank lines of credit in response to shocks that roiled credit markets in 2008 forced firms with limited financial capacity to significantly increase their prices, whereas their unconstrained counterparts slashed prices during the concomitant economic downturn.

3 Model

In this section, we develop a general equilibrium model that is qualitatively able to match the salient facts about the dynamics of producer prices during the nadir of the 2007–2009 financial crisis: the fact that financially weak firms raised prices, while their financially stronger counterparts lowered prices. To motivate the competition for market shares implied by customer markets, we consider household preferences that allow for the formation of a customer base, whereby low prices today are a form of investment into future market shares (Rotemberg and Woodford, 1991). Specifically, we adopt the good-specific habit model of Ravn et al. (2006), which we augment with nominal rigidities in the form of quadratic adjustment costs faced by firms when changing nominal prices. To explore the influence of financial frictions on the firms' price-setting behavior, our framework also includes a tractable model of costly external finance.

3.1 Preferences and Technology

The model economy contains a continuum of households indexed by $j \in [0, 1]$, and each household consumes a variety of consumption goods indexed by $i \in [0, 1]$. The preferences of households are defined over a habit-adjusted consumption bundle x_t^j and labor h_t^j as

$$\mathbb{E}_t \sum_{s=0}^{\infty} \beta^s U(x_{t+s}^j - \psi_{t+s}, h_{t+s}^j); \quad 0 < \beta < 1, \tag{4}$$

where the AR(1) demand shock ψ_t affects the final demand by altering the current marginal utility of consumption.

The consumption/habit aggregator is defined as

$$x_t^j \equiv \left[\int_0^1 \left(\frac{c_{it}^j}{s_{i,t-1}^\theta}\right)^{1-\frac{1}{\eta}} di\right]^{\frac{1}{1-\frac{1}{\eta}}}; \quad \theta < 0 \text{ and } \eta > 0, \tag{5}$$

where c_{it}^j denotes the amount of a good of variety i consumed by household j and s_{it} is the habit stock associated with good i. The good-specific habit stock is assumed to be external and thus taken as given by consumers—that is, "keeping up with the Joneses" at the good level.[16] Specifically, we assume that the external habit evolves according to

$$s_{it} = \rho s_{i,t-1} + (1-\rho)c_{it}; \quad 0 < \rho < 1. \tag{6}$$

The dual problem of cost minimization gives rise to a good-specific demand:

$$c_{it}^j = \left(\frac{p_{it}}{\tilde{p}_t}\right)^{-\eta} s_{i,t-1}^{\theta(1-\eta)} x_t^j, \tag{7}$$

where $p_{it} = P_{it}/P_t$ is the relative price of variety i in terms of $P_t = \left[\int_0^1 P_{it}^{1-\eta} di\right]^{\frac{1}{1-\eta}}$, and the externality-adjusted composite price index $\tilde{p}_t$ is given by

$$\tilde{p}_t = \left[\int_0^1 \left(p_{it} s_{i,t-1}^\theta\right)^{1-\eta} di\right]^{\frac{1}{1-\eta}}. \tag{8}$$

The supply side of the economy is characterized by a continuum of monopolistically competitive firms producing a differentiated variety of goods indexed by $i \in [0,1]$. The production technology is given by

$$y_{it} = \left(\frac{A_t}{a_{it}} h_{it}\right)^\alpha - \phi; \quad 0 < \alpha \leq 1 \text{ and } \phi > 0, \tag{9}$$

where A_t is an aggregate productivity shock and a_{it} is an adverse idiosyncratic productivity shock—that is, a cost shock—distributed as $\log a_{it} \overset{iid}{\sim} N(-0.5\sigma^2, \sigma^2)$, with the associated CDF denoted by $F(a)$. Note that we allow the production technology to exhibit either decreasing or constant returns to scale. In addition, we assume that production is subject to fixed operating costs—denoted by ϕ—which makes it possible for firms to incur negative operating income, thereby creating a liquidity squeeze if external financing is costly. Although we do not explicitly model the balance sheet of the firm, implicitly, these fixed costs can include "long-term debt payments," a coupon payment to perpetual bond holders. Thus broadly speaking, the presence of fixed operating costs captures the possibility of a debt overhang.

Firms make pricing and production decisions to maximize the present value of discounted dividends. Our timing assumptions imply that firms must commit to pricing decisions—and hence

[16] In addition to being more tractable, the assumption of external habits avoids the time-inconsistency problem of firm price setting associated with good-specific internal habits (Nakamura and Steinsson, 2011).

production—based on all aggregate information available within the period, but prior to the realization of their idiosyncratic cost shock. Based on this aggregate information, firms post prices, take orders from customers, and plan production based on *expected* marginal costs. Firms then realize actual marginal cost and hire labor to meet the demand. Labor must be paid within the period and in the presence of fixed operating costs, the firm's ex post profits may be too low to cover the total cost of production. In that case, the firm must raise external funds.

To introduce a wedge between the cost of internal and external finance in a tractable manner, we focus on equity as the sole source of external finance. That is, firms can obtain external funds only by issuing new equity, a process that involves dilution costs reflecting agency problems in financial markets. Formally, we assume that equity finance involves a constant per-unit dilution cost $\varphi_t \in (0, 1)$ per dollar of equity issued. Dilution costs are indexed by time to allow for exogenous changes in financing costs—that is, financial shocks. To keep the model tractable, we abstract from firm savings decisions by assuming that all dividends are paid out within the period.[17] This formulation of costly external finance allows us to highlight the basic mechanism within a framework that deviates only slightly from the standard good-specific habit model. In particular, in our model, all firms are identical ex ante, and as a result, only firms with an idiosyncratic cost shock above an endogenous threshold incur negative profits and are forced to issue new equity.

3.2 Profit Maximization

We now turn to the firm's problem, which, for simplicity, we describe abstracting from nominal rigidities. We then consider the implications of adding frictions to nominal price setting, which allows us to highlight the model's implications for the Phillips curve. The firm's objective is to maximize the expected present value of a dividend flow, $\mathbb{E}_0\left[\sum_{t=0}^{\infty} m_{0,t}\, d_{it}\right]$, where d_{it} denotes the (real) dividend payout when positive and equity issuance when negative and $m_{0,t}$ is the stochastic discount factor. Note that the presence of equity dilution costs φ_t implies that when a firm issues a notional amount of equity $d_{it} < 0$, actual cash intake from the issuance is reduced to $-(1 - \varphi_t)d_{it}$.

The firm's problem is subject to the flow-of-funds constraint:

$$0 = p_{it}c_{it} - w_t h_{it} - d_{it} + \varphi_t \min\{0, d_{it}\}; \tag{10}$$

and given the monopolistically competitive product markets, the demand constraint specified in equation (7). Formally, letting λ_{it}, ν_{it}, κ_{it}, and ξ_{it} denote the Lagrange multipliers associated with equations (6), (7), (9), and (10), respectively, the Lagrangian associated with the firm's problem is

[17] In our empirical analysis, we focused on the role of liquidity—as measured by cash holdings—as a determinant of firms' pricing decisions. Thus allowing for costly equity financing and precautionary cash holding is of obvious interest but would make the *distribution* of firms' liquid asset holdings a state variable. We leave this nontrivial extension for future research. However, our full model with firm heterogeneity can be thought of as representing an economy in which a certain proportion of firms have accumulated sufficient liquidity, so as to behave in an unconstrained manner. As shown in Section 5, this does not eliminate the main mechanism of our model.

given by

$$\mathcal{L} = \mathbb{E}_0 \sum_{t=0}^{\infty} m_{0,t} \Bigg\{ d_{it} + \kappa_{it} \left[\left(\frac{A_t}{a_{it}} h_{it} \right)^{\alpha} - \phi - c_{it} \right] + \xi_{it} \left[p_{it} c_{it} - w_t h_{it} - d_{it} + \varphi_t \min \{0, d_{it}\} \right]$$
$$+ \nu_{it} \left[\left(\frac{p_{it}}{\tilde{p}_t} \right)^{-\eta} s_{i,t-1}^{\theta(1-\eta)} x_t - c_{it} \right] + \lambda_{it} \left[\rho s_{i,t-1} + (1-\rho) c_{it} - s_{it} \right] \Bigg\}. \tag{11}$$

The firm's optimal choices of its decision variables are summarized by the following first-order conditions:

$$d_{it}: \quad \xi_{it} = \begin{cases} 1 & \text{if } d_{it} \geq 0 \\ 1/(1-\varphi_t) & \text{if } d_{it} < 0 \end{cases}; \tag{12}$$

$$h_{it}: \quad \kappa_{it} = \xi_{it} a_{it} \left(\frac{w_t}{\alpha A_t} \right) (c_{it} + \phi)^{\frac{1-\alpha}{\alpha}}; \tag{13}$$

$$c_{it}: \quad \mathbb{E}_t^a [\nu_{it}] = \mathbb{E}_t^a [\xi_{it}] p_{it} - \mathbb{E}_t^a [\kappa_{it}] + (1-\rho) \mathbb{E}_t^a [\lambda_{it}]; \tag{14}$$

$$s_{it}: \quad \mathbb{E}_t^a [\lambda_{it}] = \rho \mathbb{E}_t^a [m_{t,t+1} \lambda_{i,t+1}] + \theta(1-\eta) \mathbb{E}_t \left[m_{t,t+1} \mathbb{E}_{t+1}^a [\nu_{i,t+1}] \left(\frac{c_{i,t+1}}{s_{it}} \right) \right]; \tag{15}$$

$$p_{it}: \quad 0 = \mathbb{E}_t^a [\xi_{it}] - \eta \frac{\mathbb{E}_t^a [\nu_{it}]}{p_{it}}. \tag{16}$$

Implicit in the last three conditions is the assumption that the firm makes pricing and production decisions prior to the realization of the idiosyncratic cost shock a_{it}. Accordingly, these first-order conditions involve the expected shadow values of internal funds ($\mathbb{E}_t^a[\xi_{it}]$), marginal sales ($\mathbb{E}_t^a[\nu_{it}]$), and habit stock ($\mathbb{E}_t^a[\lambda_{it}]$), where the expectations are formed using all aggregate information up to time t. In contrast, the realized values ξ_{it} and a_{it} enter the efficiency conditions (12) and (13) without the expectations operator because dividend payouts (or new equity issuance) and labor hiring decisions are made after the realization of the idiosyncratic cost shock.[18]

Under risk-neutrality and with i.i.d. idiosyncratic cost shocks, the timing convention adopted above implies that firms are identical ex ante.[19] Hence, we focus on a symmetric equilibrium, in which all firms choose the identical relative price ($p_{it} = 1$), production scale ($c_{it} = c_t$), and habit stock ($s_{it} = s_t$). However, the distributions of labor inputs (h_{it}) and dividend payouts (d_{it}) are non-degenerate and depend on the realization of the idiosyncratic cost shock a_{it}.

3.3 Value of Internal Funds and the Customer Base

Define the equity issuance trigger a_t^E as the idiosyncratic cost level that satisfies the flow-of-funds constraint (10) when dividends are exactly zero:

$$a_t^E = \frac{c_t}{(c_t + \phi)^{\frac{1}{\alpha}}} \frac{A_t}{w_t}. \tag{17}$$

[18]The labor demand $h_{it} = \left(\frac{a_{it}}{A_t}\right)(c_{it} + \phi)^{\frac{1}{\alpha}}$ is substituted into equation (13) after deriving the first-order condition.

[19]A similar timing convention has been used by Kiley and Sim (2012) in the context of financial intermediation.

The first-order condition for dividends (equation 12) implies that because of costly external financing, the realized shadow value of internal funds increases from 1 to $1/(1-\varphi_t) > 1$, when the realization of the idiosyncratic cost shock a_{it} is greater than the threshold value a_t^E:

$$\xi_{it} = \begin{cases} 1 & \text{if } a_{it} \leq a_t^E \\ 1/(1-\varphi_t) & \text{if } a_{it} > a_t^E. \end{cases} \tag{18}$$

Let z_t^E denote the standardized value of a_t^E; that is, $z_t^E = \sigma^{-1}\big(\log a_t^E + 0.5\sigma^2\big)$. The expected shadow value of internal funds can then be expressed as

$$\mathbb{E}_t^a\big[\xi_{it}\big] = \int_0^{a_t^E} dF(a) + \int_{a_t^E}^{\infty} \frac{1}{1-\varphi_t} dF(a) = 1 + \left[\frac{\varphi_t}{1-\varphi_t}\right]\big[1 - \Phi(z_t^E)\big] \geq 1, \tag{19}$$

where $\Phi(\cdot)$ denotes the standard normal CDF. The expected shadow value of internal funds is strictly greater than one as long as equity issuance is costly ($\varphi_t > 0$) and the firm faces idiosyncratic liquidity risk ($\sigma > 0$). This makes the firm de facto risk averse when making its pricing decision—reducing the price lowers the markup and exposes the firm to the risk of incurring negative operating income, which must be financed through costly equity issuance.[20]

Consider first the case with no habits, so that $\theta = 0$, in which case $\lambda_{it} = 0$. By combining the first-order conditions (13), (14), and (16), we can express the pricing rule as

$$p_{it} = \frac{\eta}{\eta - 1} \frac{\mathbb{E}_t^a\big[\xi_{it} a_{it}\big]}{\mathbb{E}_t^a\big[\xi_{it}\big]} \left[\frac{w_t}{\alpha A_t}(c_{it} + \phi)^{\frac{1-\alpha}{\alpha}}\right], \tag{20}$$

where, in the symmetric equilibrium, $p_{it} = 1$ and $c_{it} = c_t$. With frictionless financial markets, $\mathbb{E}_t^a\big[\xi_{it}\big] = \mathbb{E}_t^a\big[\xi_{it} a_{it}\big] = 1$, and we obtain the standard result that firms set prices as a constant markup over marginal cost, the term in brackets.

Because the right-hand side of equation (18) is increasing in dilution cost φ_t, this mechanism introduces a form of the cost channel into the model, through which financial distortions raise marginal costs—*inclusive of expected financing costs*—and thereby reduce profit margins. Define the financially adjusted markup as the inverse of marginal cost, inclusive of expected financing costs:

$$\tilde{\mu}_t = \frac{1}{\frac{\mathbb{E}_t^a\big[\xi_{it} a_{it}\big]}{\mathbb{E}_t^a\big[\xi_{it}\big]} \left[\frac{w_t}{\alpha A_t}(c_{it} + \phi)^{\frac{1-\alpha}{\alpha}}\right]}. \tag{21}$$

The pricing rule in equation (20) then implies that, in the absence of customer markets, firms set prices as a constant markup over the *financially adjusted* marginal cost $1/\tilde{\mu}_t$.

With customer markets, $\lambda_{it} > 0$, the first-order conditions (13) and (14) imply that the value

[20] Equation (17) imposes the symmetric equilibrium. From the firm's perspective, raising prices increases profits and hence reduces the cost of external finance if $\frac{p_{it}c_{it}}{w_t h_{it}}$ is increasing in the price charged. Given the production function (9), this is true if $1 - \eta\left(1 - \frac{1}{\alpha}\frac{c_t}{c_t + \varphi_t}\right) > 0$, where η is the short-run demand elasticity. Because the term in parentheses is close to zero, this condition is satisfied in any reasonable calibration of the model.

of marginal sales ν_{it} satisfies:

$$\frac{\mathbb{E}_t^a[\nu_{it}]}{\mathbb{E}_t^a[\xi_{it}]} = \frac{\tilde{\mu}_t - 1}{\tilde{\mu}_t} + (1-\rho)\frac{\mathbb{E}_t^a[\lambda_{it}]}{\mathbb{E}_t^a[\xi_{it}]}, \tag{22}$$

where the first term measures the current price-cost margin, and the second term captures the value of the customer base.

Let $g_t \equiv c_t/s_{t-1} = (s_t/s_{t-1} - \rho)/(1-\rho)$ and define the growth-adjusted discount factor $\tilde{\beta}_{t,s+1}$ as

$$\tilde{\beta}_{t,s+1} \equiv m_{s,s+1}g_{s+1} \times \prod_{j=1}^{s-t}\left[\rho + \theta(1-\eta)(1-\rho)g_{t+j}\right]m_{t+j-1,t+j}.$$

By iterating equation (15) forward, one can solve for the marginal value of an increase in the customer base—the term $\mathbb{E}_t^a[\lambda_{it}]/\mathbb{E}_t^a[\xi_{it}]$—as the growth-adjusted present value of marginal profits. Substituting the resulting expression into equation (22) then yields the value of marginal sales:

$$\frac{\mathbb{E}_t^a[\nu_{it}]}{\mathbb{E}_t^a[\xi_{it}]} = \frac{\tilde{\mu}_t - 1}{\tilde{\mu}_t} + \chi\mathbb{E}_t\left[\sum_{s=t+1}^{\infty}\tilde{\beta}_{t,s}\frac{\mathbb{E}_s^a[\xi_{is}]}{\mathbb{E}_t^a[\xi_{it}]}\left(\frac{\tilde{\mu}_s - 1}{\tilde{\mu}_s}\right)\right], \tag{23}$$

where $\chi = (1-\rho)\theta(1-\eta) > 0$ if $\theta < 0$ and $\eta > 1$.

In a symmetric price equilibrium, equation (16) implies $\mathbb{E}_t^a[\nu_{it}]/\mathbb{E}_t^a[\xi_{it}] = 1/\eta$. With customer markets, the markup is time-varying and balances future expected marginal costs against future expected growth opportunities. The sequence of terms $\mathbb{E}_s^a[\xi_{is}]/\mathbb{E}_t^a[\xi_{it}]$, $s = t, \dots, \infty$, determines the weight that the firm places on current versus future profits when determining the expected price trajectory for its product. If today's liquidity premium outweighs the future liquidity premia, the firm places a greater weight on current profits relative to future profits and, as a result, sets a higher current markup.

3.4 Nominal Price Rigidities and the Phillips Curve

To allow for nominal rigidities, we follow Rotemberg (1982) and assume that firms face quadratic adjustment costs when changing nominal prices:

$$\frac{\gamma_p}{2}\left(\frac{P_{it}}{P_{i,t-1}} - \bar{\pi}\right)^2 c_t = \frac{\gamma_p}{2}\left(\pi_t\frac{p_{it}}{p_{i,t-1}} - \bar{\pi}\right)^2 c_t; \quad \gamma_p > 0.$$

The first-order condition governing the optimal choice of relative prices (equation 16) then imply the following local inflation dynamics:

$$\hat{\pi}_t = \frac{1}{\gamma_p}(\hat{\xi}_t - \hat{\nu}_t) + \beta\mathbb{E}_t[\hat{\pi}_{t+1}], \tag{24}$$

where $\hat{\xi}_t$ and $\hat{\nu}_t$ denote the log-deviations of $\mathbb{E}_t^a[\xi_{it}]$ and $\mathbb{E}_t^a[\nu_{it}]$, respectively. Without nominal rigidities, $\hat{\pi}_t = 0$ and consistent with equation (16), prices are set so that $\hat{\xi}_t = \hat{\nu}_t$. With nominal rigidities, equation (24) implies that given inflation expectations, the current inflation rate is determined by the expected shadow value of internal funds relative to that of marginal sales.

To highlight the relationship between the model's structural parameters and inflation dynamics, we can log-linearize equation (23) and substitute the result in equation (24). These steps yield the following expression for the Phillips curve:

$$
\begin{aligned}
\hat{\pi}_t = & -\frac{\omega(\eta-1)}{\gamma_p}\left[\hat{\tilde{\mu}}_t + \mathbb{E}_t \sum_{s=t}^{\infty} \chi \tilde{\delta}^{s-t+1} \hat{\tilde{\mu}}_{s+1}\right] + \beta \mathbb{E}_t\big[\hat{\pi}_{t+1}\big] \\
& + \frac{1}{\gamma_p}\big[\eta - \omega(\eta-1)\big] \mathbb{E}_t \sum_{s=t}^{\infty} \chi \tilde{\delta}^{s-t+1} \Big[(\hat{\xi}_t - \hat{\xi}_{s+1}) - \hat{\tilde{\beta}}_{t,s+1}\Big],
\end{aligned}
\tag{25}
$$

where $\omega = 1 - \beta\theta(1-\rho)/(1-\rho\beta)$, $\tilde{\delta} = \beta[\rho + \theta(1-\eta)(1-\rho)]$, $\hat{\tilde{\mu}}_t$ is the log-deviation of the financially adjusted markup $\tilde{\mu}_t$, and $\hat{\tilde{\beta}}_{t,s+1}$ is the log-deviation of the growth-adjusted discount factor $\tilde{\beta}_{t,s+1}$. In the absence of external habit (that is, $\theta = 0$), $\omega = 1$ and $\chi = 0$, and we obtain the standard New Keynesian Phillips curve: $\hat{\pi}_t = -\hat{\tilde{\mu}}_t + \beta\mathbb{E}_t\big[\hat{\pi}_{t+1}\big]$; in that case, current inflation is equal to the present discounted value of expected future marginal cost (that is, the inverse of the markup).

With external habit but no financial distortions (that is, $\theta < 0$ and $\varphi_t = 0$), all terms involving $\hat{\xi}_t - \hat{\xi}_{s+1}$ in the second line of equation (25) drop out. However, with customer habits, $\chi > 0$, and there are two offsetting effects of demand-driven movements in output on current inflation conditional on expected future inflation. First, the present value of future markups directly enters the Phillips curve and implies that current inflation responds to future marginal cost, conditional on the next period's expected inflation. This term increases the sensitivity of current inflation to future fluctuations in output. Second, the term $\hat{\tilde{\beta}}_{t,s+1}$ captures the capitalized growth rate of the customer base and thus measures the present value of the marginal benefit from expanding the customer base today. According to equation (25), when the firm expects a greater benefit from the future customer base, it is more willing to lower the current price in order to build its customer base. This term thus reduces the sensitivity of current inflation to future output movements. Because these two effects offset each other, customer markets may lead to more or less responsiveness of inflation to output fluctuations.

Frictions in financial markets also have two effects on inflation dynamics. First, the markup must be adjusted for the distortions that create a cost channel. Under reasonable calibrations, this adjustment reduces the countercyclicality of the markup and attenuates the response of inflation to output fluctuations—this adjustment occurs regardless of whether we allow for customer habits. Second, customer habits imply that the firm takes into account the future customer base when setting its current price. In this case, financial distortions influence the effective discount factor captured by the shadow value of dividends today relative to the future—the term $\hat{\xi}_t - \hat{\xi}_{s+1}$. In practice, however, the effect of the cost channel is small, and the primary mechanism through which financial market frictions affect inflation is by altering the discount factor associated with how the firm values the benefits of the future customer base.

Faced with both a sticky customer base and costly external finance, firms are confronted with a fundamental tradeoff between current profits and the longer-run maximization of their market share, which is reflected in the term $(\hat{\xi}_t - \hat{\xi}_{s+1}) - \hat{\beta}_{t,s+1}$. Maintaining their market share requires firms to post low current prices. However, firms may be forced to deviate from this strategy, provided that their current internal liquidity position—as summarized by $\hat{\xi}_t$—is sufficiently weak relative to their future liquidity position $\hat{\xi}_{s+1}$. In that case, firms may raise their current prices in response to an adverse demand shock in order to avoid costly external financing, a pricing strategy that resembles a myopic optimization of current profits.[21]

3.5 Closing the Model

We assume that equity issuance costs are paid out to households and hence do not affect the aggregate resource constraint. Costs incurred when firms change nominal prices are similarly returned to households in a lump-sum manner. The household's optimal consumption-savings decision then implies that the stochastic discount factor $m_{t,t+1}$ satisfies

$$m_{t,t+1} = \beta \frac{U_x(x_{t+1} - \psi_{t+1}, h_{t+1})}{U_x(x_t - \psi_t, h_t)} \frac{s_{t-1}^{\theta}}{s_t^{\theta}}. \tag{26}$$

Letting r_t denote the ex ante nominal interest rate, then the Fisher equation may be expressed as

$$1 = \mathbb{E}_t \left[m_{t,t+1} \left(\frac{1 + r_t}{1 + \pi_{t+1}} \right) \right].$$

The efficiency condition governing the household's consumption-leisure choice is given by:[22]

$$\frac{w_t}{\tilde{p}_t} = -\frac{U_h(x_t - \psi_t, h_t)}{U_x(x_t - \psi_t, h_t)}. \tag{27}$$

The endogenous aggregate state variable s_t evolves according to $s_t = \rho s_{t-1} + (1-\rho)c_t$, where, from the demand curve, the aggregate consumption index $x_t = c_t / s_t^{\theta}$.

The supply side of the model is then summarized by the markup equation (21), equation (23) governing the valuation of marginal sales, and the Phillips curve (25), along with the production function that determines labor demand, according to

$$h_t = \left[\frac{c_t + \phi}{\exp\left[0.5\alpha(1+\alpha)\sigma^2\right]} \right]^{\frac{1}{\alpha}}, \tag{28}$$

where the term in the denominator follows from the integration over the distribution of idiosyncratic

[21] The fundamental tradeoff between current cashflows and future market shares relies on the parameter restriction $\eta - \omega(\eta - 1) > 0$. Otherwise, firms in strong financial condition may *increase* their current prices in order to *increase* their long-run market shares. As long as θ, ρ, and η are chosen such that the steady-state marginal profit is strictly positive, we can exclude such pathological cases.

[22] In the numerical implementation of the model, we also assume convex adjustment costs for nominal wages (parametrized by γ_w) by introducing market power associated with differentiated labor; for expositional purposes those details have been relegated to Appendix B.

cost shocks.[23]

The model also features a monetary authority that sets the nominal interest rate r_t using a Taylor-type rule that responds to inflation and output gaps:

$$r_t = (1 + r_{t-1})^{\tau_r} \left[(1 + \bar{r}) \left(\frac{\pi_t}{\pi^*} \right)^{\tau_\pi} \left(\frac{y_t}{y_t^*} \right)^{\tau_y} \right]^{1-\tau_r} - 1. \tag{29}$$

The rule also allows for policy inertia, as reflected in letting $0 < \tau_r < 1$. In our baseline calibration of the model, we set $\tau_y = 0$, implying that monetary authorities respond only to inflation.

3.6 Calibration

A period in the model equals one quarter. Accordingly, the time discounting factor $\beta = 0.99$. Following Ravn et al. (2006), we set the deep habit parameter θ equal to -0.8. To highlight the firms' incentive to compete for market share, we also choose a fairly persistent habit formation process by assuming that only 5 percent of the habit stock is depreciated in a quarter (that is, the parameter ρ in equation (6) is set to 0.95). The CRRA parameter in the household's utility function is then set equal to 1, given that the deep habit specification provides a strong motive to smooth consumption. We set the elasticity of labor supply equal to 5.

The elasticity of substitution across varieties of differentiated goods is a key parameter in the customer markets model—smaller the degree of substitutability, greater is the firm's market power, and greater is its incentive to invest in customer base. Broda and Weinstein (2006) provide a set of estimates for the elasticity of substitution for the U.S. economy. According to their post-1990 data, the median value of the elasticity of substitution for differentiated goods at 2.1. Because this is a product category that is most relevant for the deep habits model, we set $\eta = 2$.[24]

Another important parameter is the fixed operating cost ϕ, the value of which is determined jointly with the returns-to-scale parameter α. Specifically, we set α first and then choose ϕ so that the dividend-payout ratio (relative to income) hits the post-WWII mean value of about 2.5 percent. In our calibration, $\alpha = 0.8$, a degree of returns to scale that is common in the empirical literature that relies on firm-level data, which then implies $\phi = 0.3$. With $\alpha = 0.8$, $\phi = 0.3$, and $\eta = 2$, the average gross markup in our model is equal to 1.19.

Following Cooley and Quadrini (2001), we calibrate the degree of financial market frictions—the equity dilution costs—by setting $\varphi_t = \bar{\varphi} = 0.3$. When analyzing the macroeconomic implications of financial disturbances—which we model as exogenous shocks to the time-varying equity dilution costs—we set the persistence of the financial shock to 0.9. To abstract from the differences in the persistence of different aggregate disturbances, the AR(1) parameter for the demand shock ψ_t is also

[23] The adjusted markup $\tilde{\mu}_t$ and the expected external financing cost $\mathbb{E}_t^a[\xi_{it}]$ are static functions of aggregate variables. After substituting out for these variables, the model adds two dynamic equations—a backward-looking equation for the endogenous stock of habit s_t and the forward-looking valuation equation for $\mathbb{E}_t^a[\nu_{it}]/\mathbb{E}_t^a[\xi_{it}]$—to the otherwise standard three-equation log-linearized New Keynesian model.

[24] In Appendix B, we show that the main conclusions of the paper are robust with respect to three different calibrations: (1) a lower labor supply elasticity; (2) a higher elasticity of substitution between differentiated goods; and (3) a less powerful deep-habit mechanism.

set equal to 0.9. The volatility of the idiosyncratic cost shock is calibrated at 0.05 (20 percent at an annual rate), implying a moderate amount of idiosyncratic uncertainty. With the fixed operating cost calibrated as described above, the combination of $\sigma = 0.05$ and $\bar{\varphi} = 0.3$ yields an annualized expected premium on external funds of about 13 percent (that is, $\mathbb{E}^a[\xi_i] = 1.127$). In our crisis experiment, a simulation exercise that imposes an extreme degree of financial distortions, we let $\bar{\varphi} = 0.5$, in which case, the premium on external funds jumps to 20 percent.

For the parameters related to nominal rigidities, we set the adjustment costs of nominal prices $\gamma_p = 10$ and wages $\gamma_w = 30$. These values are within the range of point estimates of 14.5 and 41 in Ravn et al. (2006), who show that deep habits substantially enhance the persistence of inflation, without the reliance on an implausibly large amount of stickiness in nominal prices.[25] Finally, we set the interest rate smoothing coefficient τ_r in the policy rule (29) at a conventional level of 0.75, and τ_π, the coefficient on the inflation gap, at 1.5, values in line with those used in the New Keynesian literature.

4 Model Simulations: Homogeneous Firms

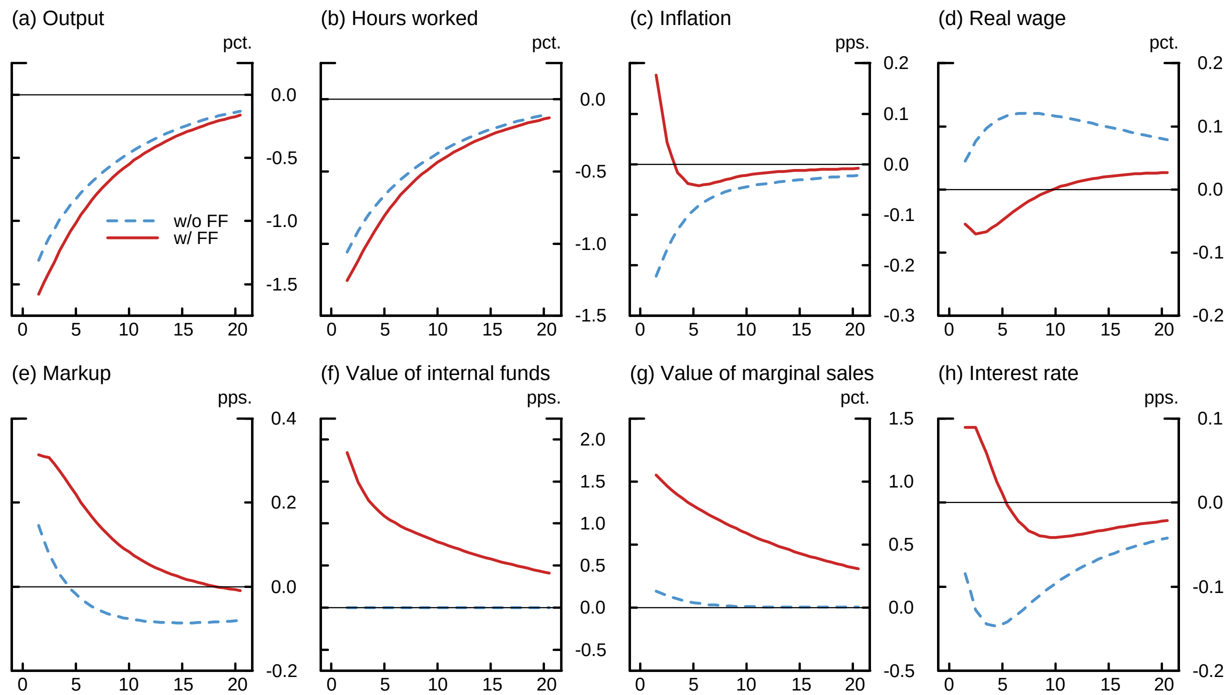
4.1 Financial Crisis and Inflation Dynamics

To implement a financial crisis in the model, we set $\varphi_t = \bar{\varphi} = 0.5$, which implies an external finance premium of 20 percent (annualized). Such a high expected cost of external funds strikes us as plausible in the latter part of 2008, a period during which the commercial paper market froze, credit spreads widened sharply, equity prices tanked, and asset price volatility skyrocketed. The solid lines in Figure 5 show the macroeconomic impact of an adverse demand shock under such extreme circumstances. To highlight the role of financial frictions, the dotted lines show the effect of the same shock in the economy with perfect capital markets.

In the absence of financial distortions, the negative demand shock leads to a drop in real output and a decline in inflation. The comparison of responses in panel (a) reveals that financial frictions amplify the response of output to a demand shock, a result consistent with the standard financial accelerator mechanism. Although differences in output dynamics are fairly modest, the initial response of inflation differs substantially across the two models. In particular, in the model with financial frictions, inflation rises rather than falls. The explanation for this striking difference can be found in panels (e)–(f). Our timing assumptions imply that firms know that the economy has been hit by a demand shock before making their pricing decisions. In the presence of financial distortions, this reduces the firms' expected cashflows and increases the probability that they will require costly external finance. As a result, the shadow value of internal funds jumps almost 200 basis points upon the impact of the shock (panel (f)). To protect themselves against the idiosyncratic tail event in which the ex post cashflows are negative and they must raise external finance, firms significantly

[25] As shown in Appendix B, setting $\gamma_p = 10$ is equivalent to assuming—in a Calvo-type price setting—that about 27 percent of firms will optimally reset their prices each quarter, a proportion that is very close to that used by standard New Keynesian models.

FIGURE 5: Demand Shock During a Financial Crisis
(*Economy with Nominal Rigidities*)



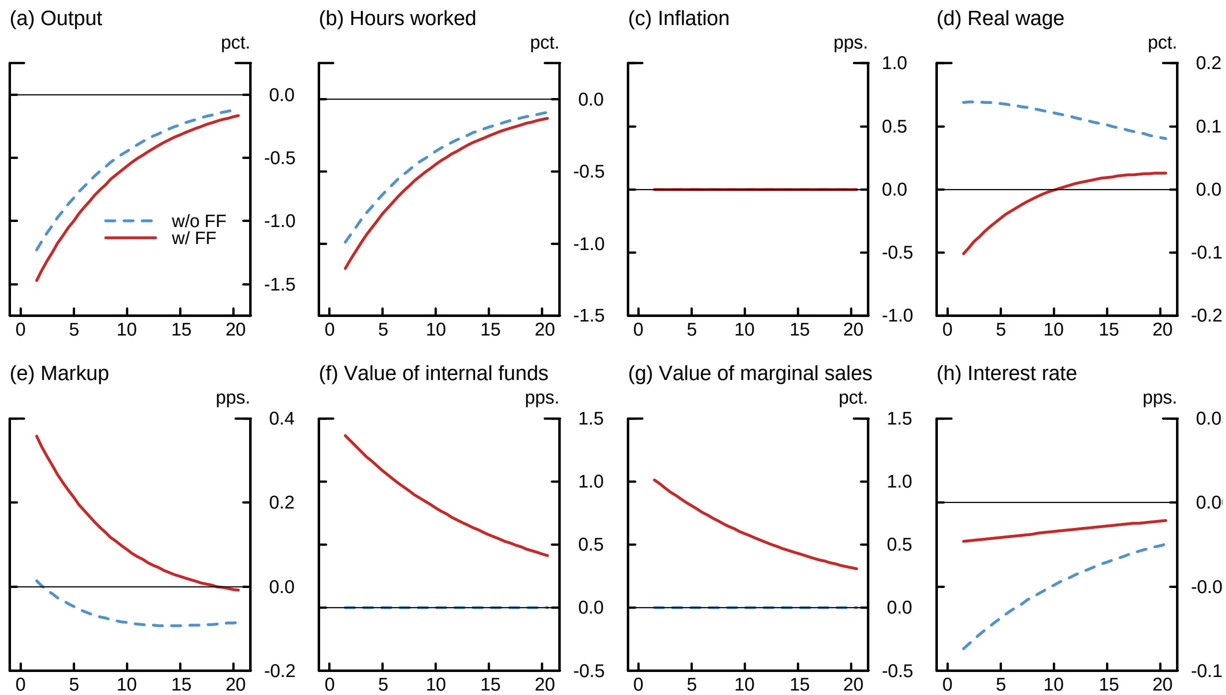
NOTE: The panels of the figure depict the model-implied responses of selected variables to a negative demand shock of 1 standard deviation: w/ FF = responses implied by a model with financial frictions, with the degree of financial frictions calibrated to a crisis situation ($\bar{\varphi} = 0.5$); and w/o FF = responses implied by a model without financial frictions ($\bar{\varphi} = 0$).

boost their markups relative to the model without financial frictions (panel (e)).

The severity of financial frictions in a crisis situation causes the value of internal funds and the value of marginal sales to move in tandem (panels (f) and (g)). Because cashflows are discounted using internal valuations, financial distortions create a direct link between the two valuations, which does not exist in an economy with frictionless financial markets. Note that in both models, the demand shock leads to a sharp initial increase in the markup (panel (e)). Financial frictions, however, substantially amplify the countercyclical behavior of markups—the increase in the markup in the model with financial distortions is double that implied by the model without such distortions. Moreover, in an economy with financial frictions, the markup remains elevated for quite some time after the initial impact of the shock, while in the frictionless case, the high initial markup is offset by low future markups. As highlighted in panels (f) and (g), the driving force behind the strong countercyclical nature of markups in the presence of financial distortions is the deterioration in the firms' internal liquidity positions, which causes firms to increase markups in an effort to stabilize near-term profits in the face of falling demand.

Figure 6 considers the same experiment, but in an environment without nominal (price and

Figure 6: Demand Shock During a Financial Crisis
(*Economy without Nominal Rigidities*)



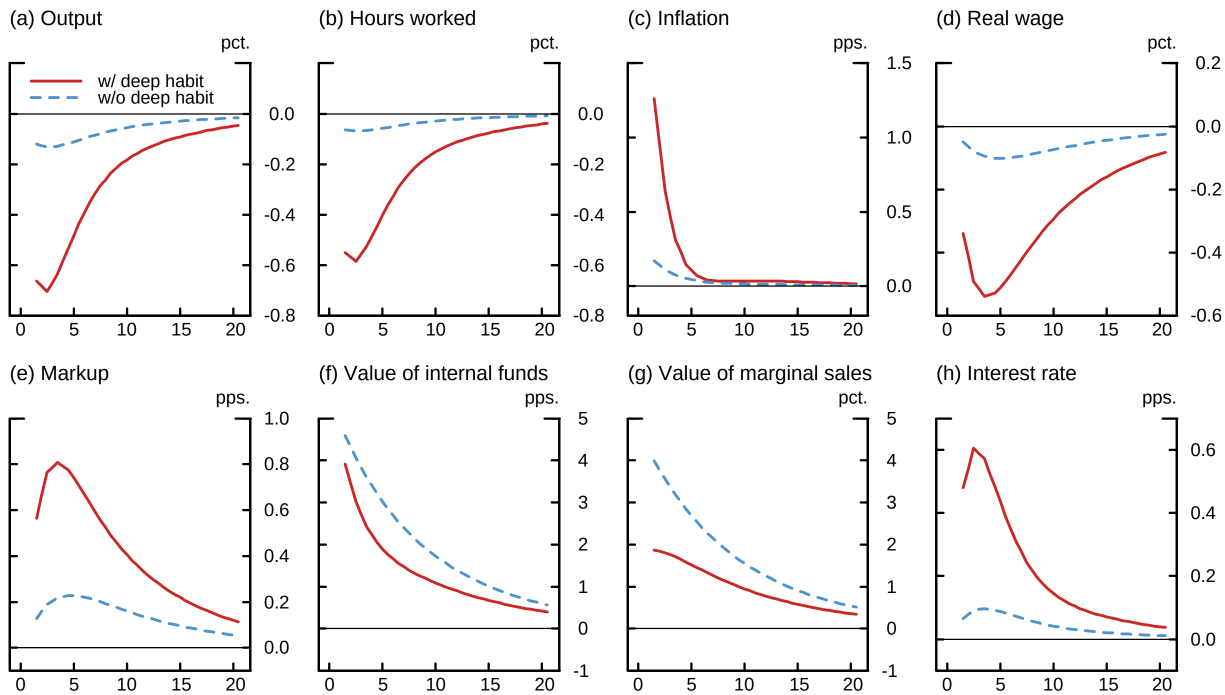
Note: The panels of the figure depict the model-implied responses of selected variables to a negative demand shock of 1 standard deviation: w/ FF = responses implied by a model with financial frictions, with the degree of financial frictions calibrated to a crisis situation ($\bar{\varphi} = 0.5$); and w/o FF = responses implied by a model without financial frictions ($\bar{\varphi} = 0$).

wage) rigidities. The negative demand shock again causes a drop in output and hours worked and, in the model with financial frictions, an increase in the value of internal funds. In the absence of financial distortions, the markup is not affected by the demand shock upon impact but then declines gradually and remains persistently below steady state. Thus, in the absence of nominal rigidities and financial distortions, the markup is strongly procyclical in response to demand shocks in this version of the deep habits model. Adding sticky prices alone to the model imparts at best only a modest degree of countercyclicality to the markup. However, with the addition of financial frictions, the markup becomes strongly countercyclical, as firms seek to increase current profits to overcome the liquidity squeeze.

4.2 Financial Shocks and Inflation Dynamics

We now consider the macroeconomic implications of financial disruptions. That is, rather than considering a reduction in demand in an environment where external finance is extremely costly, we model a financial disruption as a persistent but temporary increase in the cost of external finance. We implement this idea by assuming that the equity issuance cost parameter φ_t follows

Figure 7: Financial Shock
(*Economy with Nominal Rigidities*)



Note: The panels of the figure depict the model-implied responses of selected variables to a temporary increase in the time-varying equity dilution cost parameter φ_t: w/ deep habit = responses implied by a model with deep habits ($\theta = -0.8$); and w/o deep habit = responses implied by a model without deep habits ($\theta = 0$).

a process of the form: $\varphi_t = \bar{\varphi} f_t$, where $\log f_t = 0.90 \log f_{t-1} + \epsilon_t^f$. Using this framework, we then analyze the effects of a financial shock ϵ_t^f that increases equity dilution costs 25 percent from their steady-state level upon impact.

Under our baseline calibration ($\bar{\varphi} = 0.3$), this financial shock boosts the level of equity dilution costs from 0.3 to 0.375 upon impact, a degree of financial distortions that is significantly below that assumed in the crisis situation. The solid lines in Figure 7 show the macroeconomic implications of such a temporary increase in financial distress. To help highlight the importance of customer markets in our model, the dotted lines show the corresponding responses of the economy facing the same degree of financial distress but no customer markets—this corresponds to a financial shock in a model that incorporates only the cost-channel mechanism.

According to panels (a) and (b), the temporary increase in external financing costs has large effects on economic activity in an environment where financial distortions interact with customer markets: The immediate decline in both output and hours worked in response to a contractionary demand shock is larger by a factor of ten, compared with an economy that features only financial market frictions and thus only allows for the traditional cost channel. The response of inflation is also amplified substantially when financial frictions interact with customer markets, compared with the case where only the cost channel is present. In effect, a temporary deterioration in the firms' internal liquidity positions shrinks the financial capacity of the economy, a development that directly shifts the Phillips curve upward.

Panels (e), (f), and (g) show the essential mechanism at work. When the economy is hit by a financial shock, the markup, the shadow value of internal funds, and the value of marginal sales all increase sharply. Without customer markets, the rise in the value of internal funds is almost entirely offset by the increase in the value of an additional sale, implying very little change in the financially adjusted markup (see equation 21).[26] With customer markets, however, the financial shock enters independently as a cost-push factor in the Phillips curve because firms recognize that they may trade off current cashflows for future market share and thus are willing to increase markups.

As output falls, the habit stock declines, generating a further deterioration in the firms' liquidity positions. In effect, customer capital acts as a form of financial capital at times when internal liquidity is scarce. When habit stocks and hence output are low relative to fixed operating costs, firms are more likely to require costly external finance. Thus, the presence of customer markets generates both greater amplification and greater persistence relative to the model featuring only the standard cost-channel mechanism. As shown in panel (h), the rise in inflation also prompts an increase in the nominal interest rate in the customer markets model. Although the interest rate rule used by the monetary authorities puts zero weight on the output gap, the nominal interest rate increases by considerably less than inflation because of the interest-rate smoothing motive. This causes a sharp decline in the real interest rate. The model with customer markets, therefore, provides substantial amplification in spite of a strongly countercyclical monetary policy.

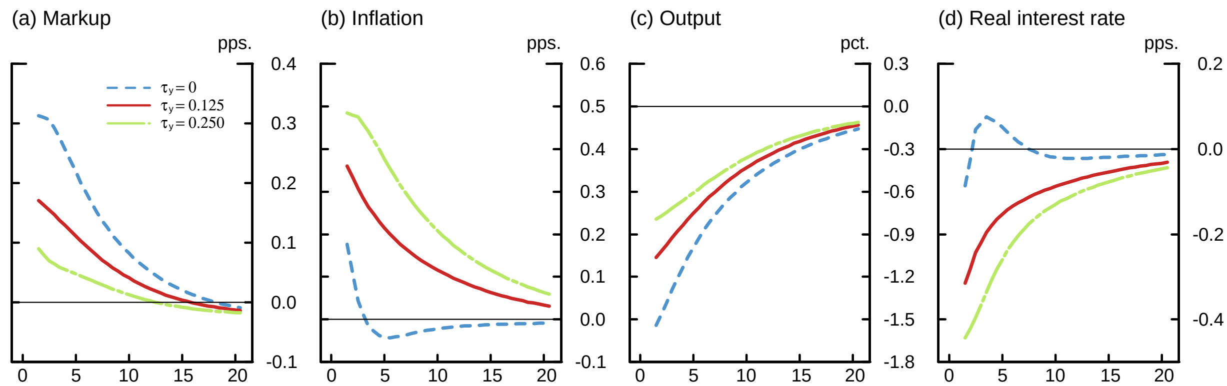
4.3 Monetary Policy Implications

According to the simulations shown in Figures 5 and 7, output falls while inflation rises in response to a contractionary demand shock or an adverse financial disturbance. These macroeconomic dynamics stand in sharp contrast to those implied by either standard New Keynesian models or financial accelerator models that work through investment demand—in both of these frameworks, output and inflation exhibit strong positive comovement in response to such shocks. Indeed, this positive comovement is at the heart of the so-called divine coincidence of monetary policy, whereby monetary authorities—by lowering nominal interest rates—can simultaneously stabilize both output and inflation and thus eliminate any concern of an active tradeoff for monetary policy.

To explore implications of our model for monetary policy, we re-consider the crisis experiment shown in Figure 5 by allowing monetary authorities to respond to inflation and output. Figure 8 reports the results of this simulation for the output gap coefficient τ_y equal to 0.125 and 0.25; for

[26] The increase in the value of marginal sales in the model with customer markets is significantly attenuated in comparison with the model without customer markets. This differential response reflects the fact that in the former model, the value of marginal sales is less responsive to shocks because it captures the entire present discounted value of the customer base. Nonetheless, the markup, and thus inflation dynamics, are determined by the gap between the value of internal funds and the value of marginal sales, which in the customer markets model widens considerably in response to a financial shock.

FIGURE 8: Demand Shock During a Financial Crisis
(*Alternative Monetary Policy Rules*)



NOTE: The panels of the figure depict the model-implied responses of selected variables to a negative demand shock of 1 standard deviation for different values of an output gap coefficient τ_y in the monetary policy rule. All responses are based on the model featuring nominal rigidities and financial frictions, with the level of financial frictions calibrated to a crisis situation ($\bar{\varphi} = 0.5$).

comparison purposes, the figure also shows the responses from the original exercise in which $\tau_y = 0$, that is, the central bank is concerned only about inflation.[27] As evidenced by the differences in the impulse responses, increasing the coefficient on the output gap successfully stabilizes output but comes at the very obvious cost of destabilizing inflation. In our model, therefore, the divine coincidence fails to hold, and there exists a meaningful tradeoff between output and inflation stabilization in response to demand and financial shocks.[28]

5 Model Simulations: Heterogeneous Firms

We now consider our full model with firm heterogeneity, which generates a nondegenerate equilibrium distribution of prices across firms in the economy. Allowing for firm heterogeneity highlights an important aspect of the interaction between customer markets and financial market frictions in periods of financial distress. In a crisis situation, financially strong firms—in response to an adverse demand shock—attempt to drive out their weaker competitors by undercutting their prices. This "price war" creates an aggregate demand externality, whereby significant heterogeneity in financial conditions across firms may lead to a greater contraction in output relative to a situation in which firms are more uniformly constrained in their financial capacity.

[27] In all three of these cases, the coefficient on the inflation gap in the policy rule $\tau_\pi = 1.5$, while the degree of interest rate smoothing $\tau_r = 0.75$.

[28] In addition to examining model sensitivity to different monetary policy rules, we have also considered the effect of a binding zero lower bound on nominal interest rates. In the model with customer markets and financial frictions, output declines lead to upward inflationary pressure. As a result, real interest rates fall by more and the amount of time spent at the zero lower bound is curtailed. Hence, the effects of a binding zero lower bound are substantially mitigated relative to a model with frictionless financial markets.

5.1 Heterogeneous Operating Costs

To introduce heterogeneity in the model, we modify the production technology in equation (9), according to

$$y_{it} = \left(\frac{A_t}{a_{it}} h_{it}\right)^{\alpha} - \phi_i, \tag{30}$$

where $\phi_i \geq 0$ denotes fixed operating costs of firm i. These costs can take on one of N-values from a set $\{\phi_1, \ldots, \phi_N\}$, where $0 \leq \phi_1 < \cdots < \phi_N$. The measure of firms with operating efficiency ϕ_k is denoted by Ξ_k, where $\sum_{k=1}^{N} \Xi_k = 1$. Lastly, we also assume that all firms face the same distribution of the idiosyncratic cost shock a_{it} (that is, $\log a_{it} \overset{iid}{\sim} N(-0.5\sigma^2, \sigma^2)$).

The introduction of heterogeneous operating costs implies that the external financing trigger is specific to each category of firms, with $d\mathbb{E}_t^a\big[\xi_{it}|\phi_k\big]/d\phi_k > 0$, $k = 1, \ldots, N$. Consistent with our empirical results, therefore, a low operating efficiency—or equivalently a high operating leverage—implies an increased likelihood that the firm will have difficulties meeting its liquidity needs using only internally generated funds. In other words, all firms within a category characterized by low operating efficiency face higher expected external financing costs and thus are considered to be financially "weak."

Within this framework, we again consider a symmetric equilibrium, in which all firms with a given level of operating efficiency choose the same price and production scale. The derivation of firm-specific prices, financing costs, labor inputs, and output decisions is analogous to the homogeneous model. In particular, firm-specific inflation rates evolve according to a category-specific Phillips curve. Note that although all firms with the same ϕ_k choose the same price level, heterogeneity in fixed operating costs generates dispersion of prices across firms. Aggregate quantities are then obtained in a standard manner. Specifically, the aggregate inflation rate can be expressed as a weighted average of inflation rates across different categories of firms:

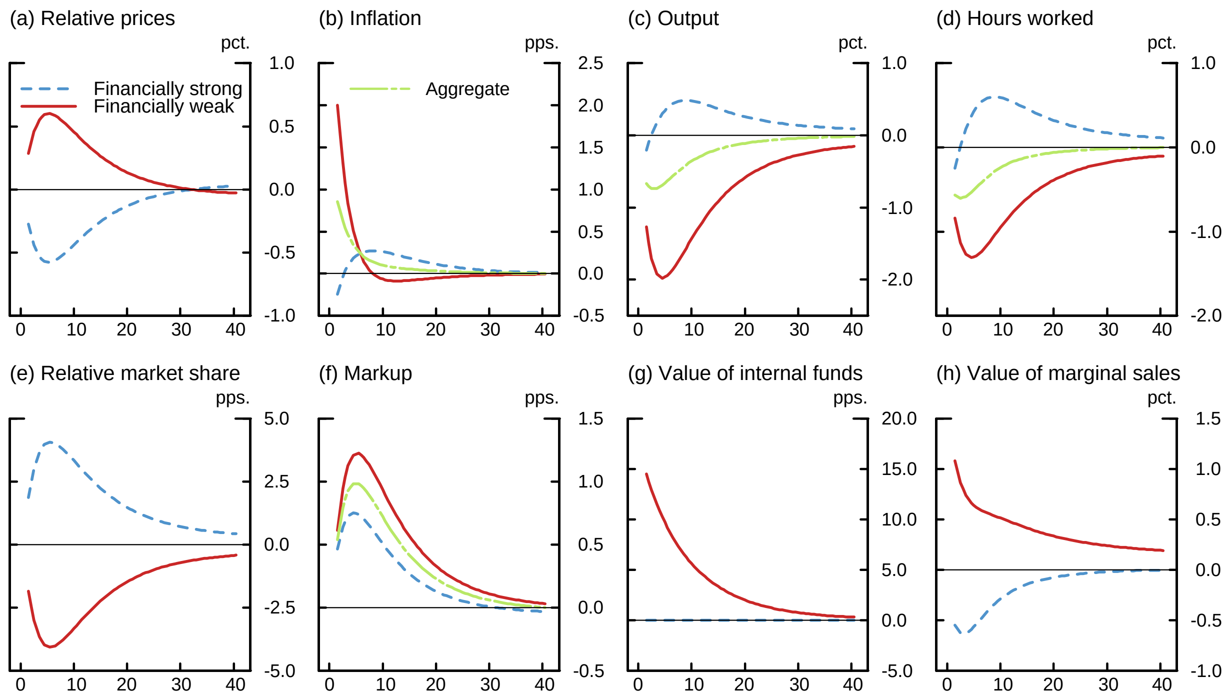
$$\pi_t = \left[\sum_{k=1}^{N} \Xi_k (p_{k,t-1}\pi_{kt})^{1-\eta}\right]^{\frac{1}{1-\eta}}, \tag{31}$$

where $\pi_{kt} \equiv P_{kt}/P_{k,t-1}$ and $p_{kt} \equiv P_{kt}/P_t$ denote category-specific inflation rates and relative prices, respectively (see Appendix B for the microfounded derivation of the aggregate inflation rate).

5.2 Countercyclical Dispersion of Inflation Rates

For maximum intuition, we consider only two categories of firms in our numerical simulations. The first consists of financially "strong" firms, which are characterized by having $\phi_1 = 0$. The second is made up of financially "weak" firms, distinguished by having $\phi_2 = 0.3$, the value used in our baseline calibration. For simplicity, we assume that the two categories are of equal sizes—that is, $\Xi_1 = \Xi_2 = 0.5$. Within this setup, we analyze the extent to which in periods of financial turmoil financially strong firms slash prices to drive out their weaker competitors. Specifically, we perturb the model economy with a financial shock, which, as in Subsection 4.2, corresponds to a temporary

Figure 9: Financial Shock
(*Economy with Heterogeneous Firms*)



Note: The panels of the figure depict the model-implied responses of selected variables to a temporary increase in the time-varying equity dilution cost parameter φ_t. The sector consisting of financially strong firms is defined by the operating efficiency level $\phi_1 = 0$, whereas the sector consisting of financially weak firms has the operating efficiency level $\phi_2 = 0.3$. The aggregate responses are computed under the assumption that the two sectors are of equal sizes.

increase in equity dilution costs from their normal level ($\bar{\varphi} = 0.3$).

The solid line in panel (a) of Figure 9 shows the response of relative prices ($p_{kt} = P_{kt}/P_t$) for financially weak firms, whereas the dashed line depicts the corresponding response of their financially strong counterparts. In response to an adverse financial shock, financially healthy firms cut their prices—behavior consistent with the concurrent decline in aggregate output—while the financially vulnerable firms actually increase their prices in an effort to avoid costly external financing. Panel (b) translates this difference in the price-setting behavior into the category-specific inflation rates ($\pi_{kt} = P_{kt}/P_{k,t-1}$). Clearly evident is the countercyclical behavior of the dispersion in inflation rates, a result consistent with that documented by Vavra (2014).[29]

Panel (c) shows the dynamics of output. As a result of "winning" the price war, financially strong firms gradually expand output in order to satisfy the growing demand engendered by the relative price cut. Financially weak firms, by contrast, slash production, a move that causes the

[29] In our case, the countercyclical dispersion in inflation rates arises endogenously in response to the differences in financial conditions across firms, whereas Vavra (2014) relies on an exogenous second-moment (that is, uncertainty) shock that is calibrated to be countercyclical.

aggregate output and hours worked to decline moderately. Again, the dispersion in output and hours worked at the micro level is generated endogenously by the distortions in financial markets.

The dynamics of the relative market shares for the two categories of firms are shown in panel (e). Consistent with their aggressive pricing behavior, financially healthy firms significantly expand their market share during the economic downturn. Moreover, the customers that switched products during the downturn form a loyal group, as a substantial part of them stays with the new products, even after the relative prices of the goods produced in the two sectors return to their respective steady-state levels. For example, after 20 quarters, the relative prices charged by financially strong firms are for all practical purposes back to their normal level, but their relative market share remains elevated, which highlights the primary reason why undercutting competitors' prices can be such a profitable investment.

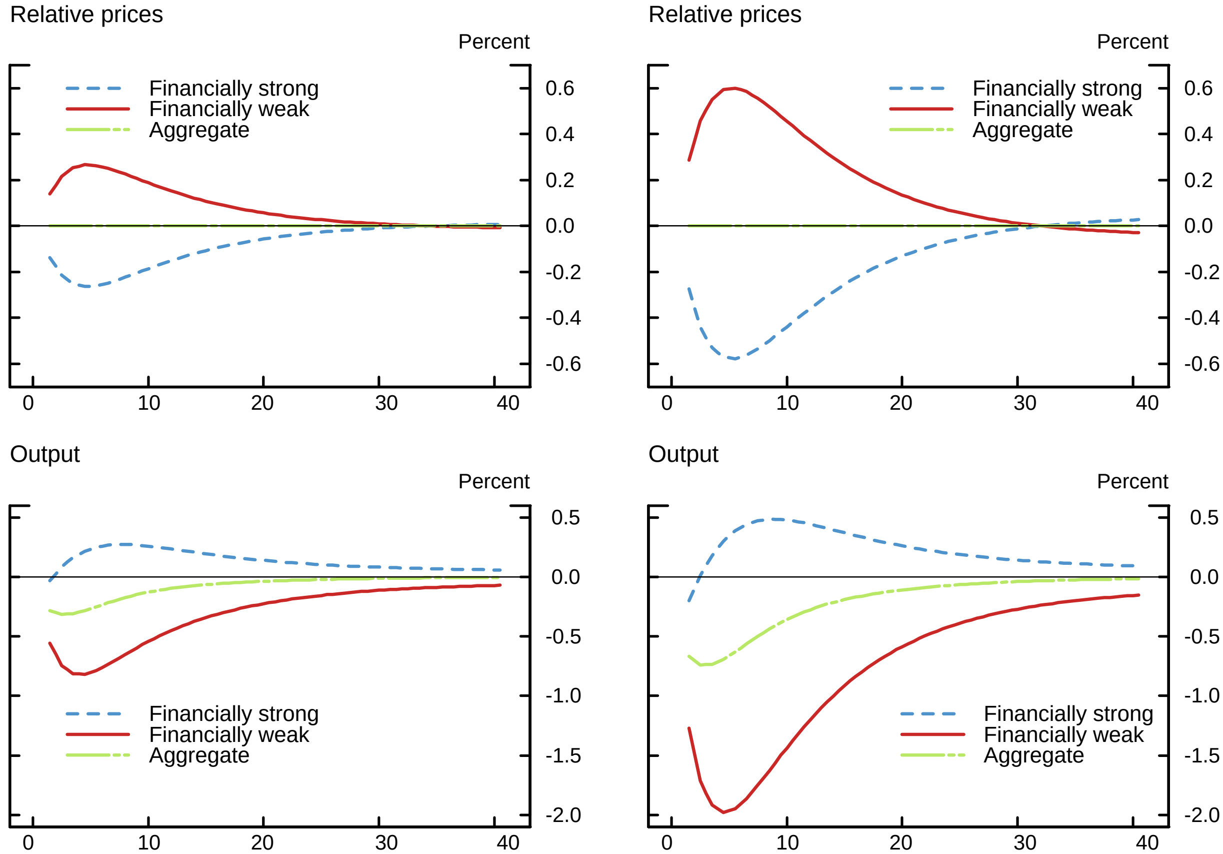
5.3 The Paradox of Financial Strength

The above example highlights the willingness of firms with strong balance sheets to undercut prices of firms with weak balance sheets during economic downturns. We now consider whether firms with ample financial capacity can slash their prices so aggressively that they drive out the financially weaker firms to such an extent so as to generate a sizable drop in aggregate output. Such a scenario can be implemented in different ways. One way is to make the contribution of the habit to the final demand more important and more persistent by choosing higher values for θ and ρ. Alternatively, we can reduce the price elasticity of demand by lowering η. We follow the first approach and set $\theta = -0.85$ and $\rho = 0.985$, compared with the baseline values of $\theta = -0.8$ and $\rho = 0.9$.

Using this new calibration, we consider two model economies, distinguished only by the degree of heterogeneity in the firms' financial capacity. In the first economy, termed a financially fragile economy, we assume that $\phi_1 = 0.8\phi_2$ with $\phi_2 = 0.3$; the second economy—termed a financially robust economy—has $\phi_1 = 0$ and $\phi_2 = 0.3$. In both economies, the two categories of firms are of the same size. Note that the financially fragile economy features a greater proportion of firms with limited financial capacity. However, there is considerably less heterogeneity in financial capacity across firms in that case. The dynamics of relative prices and output in response to our standard financial shock are depicted Figure 10.

The paradox of financial strength can be seen from the fact that a financially fragile economy (panel (a)) experiences a noticeably less severe decline in aggregate output in response to an adverse financial shock, compared with the economy that overall has greater financial capacity but more pronounced heterogeneity in the relative strength of the firms' balance sheets (panel (b)). By comparing the top two panels, one can see that this difference reflects the inability of financially strong firms in the financially fragile economy to cut prices as aggressively as their counterparts in the financially robust economy: The price cut by financially strong firms in the former economy is less than one-half of that implemented by the financially strong firms in the latter economy. According to the bottom two panels, the aggressive pricing strategy of financially healthy firms in the case with greater heterogeneity in financial conditions is a Pyrrhic victory because it drives down

Figure 10: The Paradox of Financial Strength
(*Economy with Heterogeneous Firms*)



(a) Financially fragile economy (b) Financially robust economy

Note: Panels of the figure depict the model-implied responses of selected variables to a temporary increase in the time-varying equity dilution cost parameter φ_t. Panel (a): Financially fragile economy corresponds to a model with $\phi_1 = 0.8\phi_2$, with $\phi_2 = 0.3$; and Panel (b): Financially robust economy corresponds to a model with $\phi_1 = 0$ and $\phi_2 = 0.3$. In both cases, financially strong firms are in category 1, which is characterized by the operating efficiency level ϕ_1; financially weak firms, in contrast, operate in category 2 with the efficiency level ϕ_2. The aggregate responses are computed under the assumption that the two categories of firms are of equal sizes.

the output of financially weak firms to such an extent that the economy experiences a significantly more severe economic slump than in the case with less heterogeneity but an overall greater degree of financial fragility.[30]

[30]This finding also suggests that macroeconomic stabilization policies aimed at providing liquidity support to financially vulnerable firms during periods of financial distress may offer an effective tool to avoid a severe deterioration in economic activity associated with credit cycles.

6 Conclusion

This paper analyzes inflation dynamics during the recent financial crisis through the lens of customer markets theory, while dispensing with the assumption of frictionless financial markets. The theoretical exploration of this mechanism is motivated by new empirical evidence, which shows that firms with limited internal liquidity significantly increased their prices in 2008, a period characterized by the widespread disruptions in credit markets and a sharp contraction in output.

To explore theoretically the macroeconomic implication of financial frictions in customer markets, we develop a general equilibrium model, in which monopolistically competitive firms face costly price adjustment and costly external finance, while setting prices to actively manage current versus future expected demand. In this environment, a firm's desire to preserve internal liquidity and to avoid costly external finance creates an incentive to raise prices in response to adverse demand or financial shocks. In economic booms, by contrast, the competition for market shares mitigates the upward pressure on prices. The combination of financial frictions and customer markets thus strengthens the countercyclical behavior of markups and significantly attenuates the response of inflation to demand and financial shocks.

Allowing for differences in financial conditions across firms, our model simulations show that in response to an adverse financial shock, firms with limited financial capacity raise prices relative to their financially stronger counterparts, pricing behavior observed during the nadir of the financial crisis in 2008. The price cuts by firms with strong balance sheets and the resulting gains in their market share lead to a further deterioration in the liquidity position of financially constrained firms, which amplifies the decline in aggregate output. Both empirical results and model simulations thus support the notion that in periods of widespread financial distress, the interaction of customer markets with financial frictions can significantly dampen the downward pressure on prices and account for the stabilization of inflation in the face of significant and long-lasting economic slack.

Combining customer markets theory with financial market frictions also has important implications for the conduct of monetary policy. In the absence of financial frictions, inflation and output exhibit strong comovement and reducing nominal interest rates successfully stabilizes inflation and output in response to negative demand or financial shocks. With financial distortions, however, adverse demand and financial shocks shift the Phillips curve upwards. As a result, the divine coincidence fails to hold, and monetary authorities face an active tradeoff between inflation and output stabilization in response to both demand and financial disturbances.

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Appendices – For Online Publication

This Online Appendix consists of two parts: Data Appendix (Appendix A) and Model Appendix (Appendix B).

A Data Appendix

The Data Appendix consists of two subsections. Subsection A.1 compares the pricing patterns in the matched PPI–Compustat sample with those in the full PPI sample; it also describes the construction of our key Compustat variables and compares the various firm characteristics for our sample of firms with those of the entire U.S. nonfinancial corporate sector. Subsection A.2 documents the effects of internal liquidity on other aspects of firms' behavior (i.e., employment, capital investment, R&D expenditures, and inventory accumulation).

A.1 Full PPI vs. Matched PPI–Compustat Samples

Compared with the full PPI sample, the matched PPI–Compustat panel is more heavily concentrated on the manufacturing sector (2-digit NAICS 31–33). More than 90 percent of goods in the matched PPI–Compustat data set are produced by manufacturing firms, compared with about 60 percent in the full PPI data set. Table A-1 compares the key cross-sectional price-change characteristics between the full PPI and matched PPI–Compustat data sets. In the first step, we calculate the *average* price-change characteristic for each good; in the case of good-level inflation, for example, we compute $\pi_{i,j,\cdot} = T_i^{-1} \sum_{t=1}^{T_i} \pi_{i,j,t}$, where T_i denotes the number of months that good i is in the sample. In the second step, we compute the summary statistics of the average good-specific price change characteristics for the two data sets.

An average establishment in the PPI–Compustat panel reports in an average month price information on 5.4 goods, whereas its counterpart in the full PPI panel does so for 4.3 goods. In addition, prices of goods produced by the former are, on average, sampled over a longer time period—51.2 months compared with 42.3 months. Despite these differences, the cross-sectional price change characteristics are very similar across the two samples. The price of an average good in the full PPI panel increases 0.15 percent per month, on average, over its lifetime in the sample, compared with 0.12 percent for an average good in the PPI–Compustat panel. Not surprisingly, the dispersion of average good-level inflation rates in the full PPI sample is noticeably higher than that in the matched PPI–Compustat sample, reflecting the fact that the former sample contains many goods with very volatile prices. In both data sets, the distributions of positive and negative price changes are also very comparable: The median of the average good-specific positive inflation rates is 5.2 percent for the full PPI sample and 4.8 percent for the matched PPI–Compustat sample; the corresponding medians of the average good-specific negative inflation rates are −4.8 percent and −4.4 percent, respectively.

On average, the probability with which prices of an average good are adjusted in the full PPI panel is 16 percent per month, compared with 18 percent per month for the PPI–Compustat panel; that is, an average good changes its price about every 6 months in both data sets. However, as evidenced by the associated standard deviations, the frequency of price changes varies significantly across goods, a pattern also documented by Nakamura and Steinsson (2008). Consistent with a positive average inflation rate in both panels, the average frequency of upward price changes exceeds that of the downward price changes in both cases.

We now describe the construction of firm-specific indicators based on the quarterly Compustat data. In variable definitions, x_n denotes the Compustat data item n.

- **Cash and Short-Term Investments** (x_{36}): cash and all securities readily transferable to cash as listed in the current asset section of the firm's balance sheet.
- **Selling, General, and Administrative Expenses** (x_1): all commercial expenses of operation incurred in the regular course of business.
- **Net Sales** (x_2): gross sales (the amount of actual billings to customers for regular sales completed during the quarter) less cash discounts, trade discounts, returned sales, and allowances for which credit is given to customers.
- **Cost of Goods Sold** (x_{30}): all costs directly allocated by the company to production, such as material, labor, and overhead. Selling, General, and Administrative Expenses are not included in the cost of good sold.
- **Total Assets** (x_{44}): current assets plus net property, plant & equipment, plus other noncurrent assets.

The *liquidity ratio* is defined as the ratio of cash and short-term investments in quarter t to total assets in quarter t ($x_3[t]/x_{44}[t]$), and the *SGAX ratio* is defined as the ratio of selling, general, and administrative expenses in quarter t to sales in quarter t ($x_1[t]/x_2[t]$). To ensure that our results were not influenced by a small number of extreme observations, we deleted from the quarterly Compustat panel data set all firm/quarter observations that failed to satisfy any of the following criteria:

1. $0.00 \leq$ Liquidity Ratio ≤ 1.00;
2. $0.00 \leq$ SGAX Ratio ≤ 10.0;
3. $-2.00 \leq \Delta \log(\text{Net Sales}) \leq 2.00$;
4. $-2.00 \leq \Delta \log(\text{Cost of Goods Sold}) \leq 2.00$.

Table A-2 contains the selected summary statistics for the key variables used in the analysis for both the matched PPI–Compustat sample and for all U.S. nonfinancial firms covered by Compustat. In general, the PPI–Compustat sample contains larger firms—the median firm size, as measured by (quarterly) real sales, is more than \$300 million, compared with only about \$80 million for the entire Compustat sample. Reflecting their larger size, the firms in the PPI–Compustat panel tend to grow more slowly, on average, and also have less volatile sales. The difference in average firm size between the two data sets helps explain the fact that the aggregate dynamics of sales and prices of firms in the PPI–Compustat sample are representative of broader macroeconomic trends (see Figure 1 in the main text).

In terms of financial characteristics, the two sets of firms are fairly similar, especially if one compares the respective medians of the two distributions. Nevertheless, firms in the PPI–Compustat sample tend to have somewhat less liquid balance sheets, on balance, as measured by the liquidity ratio. This difference is consistent with the fact that the PPI–Compustat sample consists of larger firms that, ceteris paribus, have better access to external sources of finance and therefore less need to maintain a precautionary liquidity buffer. An average firm in the PPI–Compustat sample also tends to have a lower SGAX ratio compared with an average nonfinancial firm in Compustat.

As noted in the main text, when sorting firms into low and high liquidity categories in month t, we rely on the trailing average liquidity ratio over the preceding 12 months. When sorting firms into low and high SGAX categories, by contrast, we rely on the average SGAX ratio computed over the 2000–2004 pre-sample period. Table A-3 summarizes the first two moments of the (good-level) price change characteristics—measured from month $t-1$ to month t—for the various categories of firms over the 2005–2012 sample period.

Focusing first on the financial dimension—the top panel—prices of goods produced by firms with relatively ample internal liquidity increase at a slower rate, on average, compared with prices of goods produced by their low liquidity counterparts. In an accounting sense, the average inflation differential of 12 basis points per month reflects the fact that the average price decline at high liquidity firms is about 6.2 percent per month, whereas at low liquidity firms, the average price decline is only 5.5 percent. These differences in the average inflation rates between financially strong and weak firms do not reflect differences in the extensive margin of price adjustment, as the average frequency of price changes—both overall and directional—is very similar between the two types of firms. Finally, as noted in the *Memo* item, low liquidity firms have, on average, a significantly less liquid balance sheets compared with their high liquidity counterparts: in the former category, liquid assets account, on average, for only 3 percent of total assets, compared with 21 percent in the latter category.

As shown in the bottom panel of the table, pricing dynamics also differ across firms with varying intensity of SG&A spending. Prices of goods produced by firms with a high SGAX ratio are estimated to rise at an average rate of only 4 basis points per month, compared with an 18 basis points rate of increase at firms with a low SGAX ratio. This systematic inflation differential primarily reflects larger average price cuts by the high SGAX-ratio firms (6.5 percent), compared with those at the low SGAX-ratio firms (5.5 percent). The intensity of SG&A spending is also correlated with the frequency with which firms adjust their prices. On average, high SGAX-ratio firms exhibit a markedly lower frequency of price adjustment compared with their low SGAX-ratio counterparts (7 percent vs. 14 percent); moreover this difference extends to both positive and negative price changes. As indicated by the *Memo* item, the average SGAX ratio over our sample period differs significantly between the two types of firms, in a manner that is consistent with our ex ante classification.

Panel (a) of Figure A-1 shows the industry-adjusted inflation rates of low and high liquidity firms within the durable and nondurable goods manufacturing sectors, while panel (b) displays the same information for firms with varying intensity of SG&A spending. This analysis is based on a subset of the matched PPI-Compustat data set, though, as noted in Section 2 of the main text, more than 90 percent of goods in the matched PPI–Compustat data set are produced by manufacturing firms, split about evenly between durable and nondurable goods producers.

A.2 Liquidity, Employment, and Investment During the Financial Crisis

In this section, we document that differences in the firms' internal liquidity positions—as measured by the liquidity ratio—had a differential effect not only on their price-setting behavior, but also on their employment and other more traditional forms of investment (i.e., expenditures on fixed capital and research and development (R&D) and inventory accumulation).

To examine formally the role of internal liquidity in employment dynamics, we use the annual Compustat data for the sample of matched PPI-Compustat firms to estimate the following fixed effects panel regression:

$$\Delta \log E_{j,t+1} = \beta \text{LIQ}_{j,t} + \theta \Delta \log \tilde{S}_{j,t+1} + \eta_j + \lambda_{t+j} + \epsilon_{j,t+1}, \quad \text{(A-1)}$$

where $\Delta \log E_{j,t+1}$ denotes the log-difference in the number of employees at firm j from year t to year $t+1$, and $\Delta \log \tilde{S}_{j,t+1}$ is the corresponding log-difference in the firm's real sales, as defined in the main text.[31] With regards to capital and R&D expenditures, we estimate:

$$\log \left[\frac{x}{K} \right]_{j,t+1} = \beta \mathrm{LIQ}_{j,t} + \boldsymbol{\theta}' \mathbf{Z}_{j,t+1} + \eta_j + \lambda_{t+1} + \epsilon_{j,t+1}, \tag{A-2}$$

where, if $x = I$, $[I/K]_{j,t+1}$ denotes the ratio of capital expenditures of firm j during year $t+1$ to its capital stock at the end of year t, and if $x = \mathrm{RD}$, $[\mathrm{RD}/K]_{j,t+1}$ denotes the ratio of R&D expenditures during year $t+1$ relative to capital stock at the end of year t.[32] In all specifications, $\mathrm{LIQ}_{j,t}$ denotes the firm's liquidity ratio at the end of year t, a timing convention that is consistent with our benchmark pricing regressions in the main text.

The inclusion of the current growth in real sales $\Delta \log \tilde{S}_{j,t+1}$ in the employment regression (A-1) captures the firm-specific cyclical factors associated with employment fluctuations, while the vector $\mathbf{Z}_{j,t+1}$ in equation (A-2) controls for the firm's investment opportunities. In line with the previous empirical literature (Himmelberg and Petersen, 1994; Gilchrist and Himmelberg, 1998; Gilchrist and Zakrajšek, 2007), we measure investment fundamentals using the log of the operating-income-to-capital ratio in year $t+1$, denoted by $[\Pi/K]_{j,t+1}$.[33] One drawback of this measure is that it is not explicitly forward looking. Accordingly, we also include the log of Tobin's Q—measured as of the end of year t—in the vector of fundamentals $\mathbf{Z}_{j,t+1}$. Because it is based on the firm's equity valuations, Tobin's Q is a forward-looking variable and thus contains information about future investment opportunities that may not captured by the firm's current profit rate.

When analyzing the role of internal liquidity as a determinant of cyclical fluctuations in inventory investment, we can work with quarterly, as opposed to annual, data. In that case, we estimate the following specification:

$$\Delta \log N_{j,t+1} = \beta \mathrm{LIQ}_{j,t} + \theta_1 \log \left[\frac{N}{S} \right]_{j,t} + \theta_2 \Delta \log N_{j,t} + \theta_3 \Delta \log S_{j,t} + \eta_j + \lambda_{t+1} + \epsilon_{j,t+1}, \tag{A-3}$$

where $\Delta \log N_{j,t+1}$ denotes the log-difference of (total) inventories from quarter t to quarter $t+1$, and $\log[N/S]_{j,t}$ is the log of the firm's inventory-to-sales ratio in quarter t. This "error-correction" specification implicitly assumes the the firm's target (log) inventory-to-sales ratio consists of a time-invariant firm-specific component—subsumed into the firm fixed effect η_j—and a time-varying aggregate component, captured by the time fixed effect λ_{t+1} (Calomiris et al., 1995; Carpenter et al., 1998).

We estimate regressions (A-1), (A-2) and (A-3) by OLS, using the "within" transformation to eliminate firm fixed effects.[34] The results of this exercise are tabulated in Table A-4. As shown in columns (1), (3), (5), and (7), differences in the firms' internal liquidity positions are an important determinant—both economically and statistically—of differences in employment growth, capital accumulation, R&D expenditures, and inventory investment across firms over the 2005–2012 period. According to the estimates reported in those columns, a difference in the liquidity ratio of 10 percentage point between two firms in year t—a difference of less than one standard deviation

[31] Similar employment regressions were estimated by Sharpe (1994). Note that because the micro-level producer prices used to construct real sales growth at the firm level start in January 2005, the time-series dimension of the resulting annual panel runs from 2006 to 2012.

[32] We use the log transformation of the dependent variables because $[I/K]_{j,t+1}$ and $[\mathrm{RD}/K]_{j,t+1}$ are positively skewed, which may induce heteroskedasticity in the error term $\epsilon_{j,t+1}$ across firms.

[33] Because operating income may be negative, we use the transformation $\log(c + [\Pi/K]_{j,t+1})$, where c is chosen so that $c + [\Pi/K]_{j,t+1} > 0$, for all j and t.

[34] We applied a set of standard filters to the data in order to eliminate extreme observations.

(see Table A-2)—is associated with a differential growth of employment of about 3.5 percentage points over the subsequent year. Such a difference in the firms' internal liquidity also translates into more than a 25 percentage point differential in the investment rate between financially weak and strong firms and a 22 percentage point differential in R&D expenditures, relative to capital, over the same period. The effects of internal liquidity on inventory accumulation are also sizable in economic terms: a 10 percentage point difference in the liquidity ratio across firms in quarter t implies a difference in the growth of inventory stocks of 2.3 percentage points (at an annual rate) over the subsequent quarter.

These results strongly support our hypothesis that firms holding less liquid assets not only increased prices during the recent financial crisis, but they also slashed employment, cut back capital and R&D spending, and reduced inventory stocks by significantly more than their liquidity unconstrained counterparts. Our empirical results are also consistent with the survey evidence compiled by Campello et al. (2010), who report that in 2008, companies in the U.S., Europe, and Asia that identified themselves as credit constrained planned to lay off significantly more workers and make substantially deeper cuts in their capital and tech spending than companies that categorized themselves as credit unconstrained.

Columns (2), (4), (6), and (8) of the table report the results from specifications in which the coefficient on the liquidity ratio is allowed to differ between the crisis ($\mathbf{1}[\text{CRISIS}_t = 1]$) and non-crisis ($\mathbf{1}[\text{CRISIS}_t = 0]$) periods.[35] According to column (2), the firms' internal liquidity positions had, in economic terms, an appreciably larger effect on employment in 2008 and 2009—the coefficient on the liquidity ratio during the crisis period is 0.418, compared with the non-crisis estimate of 0.346. Moreover, the same sort of asymmetry appears to be also evident in the case of inventory investment (column 8). Thus, employment and inventories become markedly more sensitive to corporate liquidity during the crisis period. As argued by Bils and Kahn (2000), these results provide further evidence that markups of liquidity constrained firms become more countercyclical in periods of widespread turmoil in financial markets.

[35] For specifications that rely on annual data (columns (1)–(4)), the crisis indicator is equal to 1 in 2008 and 2009 (and 0 otherwise), reflecting the fact that the firm-level annual data are reported at fiscal year-ends. For specifications that rely on quarterly data (columns (5) and (6)), the crisis indicator is equal to 1 in 2008 (and 0 otherwise), a definition that is consistent with the pricing regressions reported in Tables 1 and 2 in the main text.

Table A-1: Summary Statistics of Good-Level Price Change Characteristics
(*Full PPI Sample vs. Matched PPI–Compustat Sample*)

Variable (percent)	Mean	STD	Min	P50	Max
Inflation					
Full PPI sample	0.15	0.82	−42.80	0.02	55.59
PPI–Compustat sample	0.12	0.57	−7.15	0.08	5.04
Positive price changes					
Full PPI sample	7.52	0.26	0.00	5.21	99.32
PPI–Compustat sample	6.21	6.19	0.00	4.80	89.45
Negative price changes					
Full PPI sample	−7.72	9.73	−99.88	−4.76	−0.00
PPI–Compustat sample	−6.70	8.39	−88.53	−4.38	−0.00
Freq. of price changes					
Full PPI sample	15.52	25.90	0.00	4.88	100.00
PPI–Compustat sample	18.31	27.28	0.00	6.90	100.00
Freq. of positive price changes					
Full PPI sample	9.14	14.45	0.00	3.45	100.00
PPI–Compustat sample	10.44	14.67	0.00	4.76	75.00
Freq. of negative price changes					
Full PPI sample	6.37	13.09	0.00	0.00	100.00
PPI–Compustat sample	7.87	13.68	0.00	1.52	100.00
Avg. number of goods per firm					
Full PPI sample	4.3	2.6	1	4	77
PPI–Compustat sample	5.4	3.3	1	4.9	41
Months in the panel					
Full PPI sample	42.3	25.3	1	41	96
PPI–Compustat sample	51.2	20.2	1	52	95

Note: Sample period: monthly data from Jan2005 to Dec2012. Full PPI sample: No. of goods = 202,281; No. of respondents = 46,306; and Obs. = 8,551,681. Matched PPI–Compustat sample: No. of goods = 6,859; No. of respondents = 1,242; and Obs. = 351,192. All price change characteristics correspond to good-level averages computed using trimmed monthly data.

Table A-2: Summary Statistics for Selected Firm Characteristics
(*U.S. Nonfinancial Corporate Sector vs. Matched PPI–Compustat Sample*)

Variable	Mean	STD	Min	P50	Max
Sales ($bil.)[a]					
Compustat sample	0.96	4.44	<.01	0.08	200.25
PPI–Compustat sample	1.69	5.71	<.01	0.33	125.26
Liquidity ratio					
Compustat sample	0.21	0.24	0.00	0.12	1.00
PPI–Compustat sample	0.15	0.16	0.00	0.09	1.00
SGAX ratio					
Compustat sample	0.39	0.59	0.00	0.25	8.00
PPI–Compustat sample	0.26	0.29	0.00	0.21	7.77
Sales growth (pct.)					
Compustat sample	1.51	29.67	−199.87	2.11	199.92
PPI–Compustat sample	1.06	19.36	−196.52	1.83	176.88
COGS growth (pct.)					
Compustat sample	1.32	29.47	−199.80	2.03	199.86
PPI–Compustat sample	0.82	19.72	−187.27	1.70	177.74

Note: Sample period: Jan2005 to Dec2012 at a quarterly frequency. Compustat sample (U.S. nonfinancial sector): No. of firms = 6,138 and Obs. = 152,944. Matched PPI–Compustat sample: No. of firms = 584 and Obs. = 16,052. Liquidity ratio = cash & short-term investments to total assets; SGAX ratio = sales & general administrative expenses (SGAX) relative to sales; and COGS = cost of goods sold. All statistics are based on trimmed data.
[a] Deflated by the U.S. nonfarm business sector GDP price deflator (2009:Q4 = 100).

TABLE A-3: Summary Statistics of Price Change Characteristics
(*By Selected Firm Characteristics*)

Variable (percent)	Low Liquidity Firms Mean	Low Liquidity Firms STD	High Liquidity Firms Mean	High Liquidity Firms STD
Inflation	0.17	4.09	0.05	4.62
Positive price changes	5.45	6.97	5.46	7.82
Negative price changes	−5.52	7.89	−6.18	10.02
Freq. of price changes	19.90	39.92	19.00	39.23
Freq. of positive price changes	11.56	31.97	10.56	30.73
Freq. of negative price changes	8.34	27.64	8.44	27.80
No. of goods	5,011		3,956	
Observations	189,277		123,220	
Memo: Liquidity ratio	0.03	0.05	0.21	0.17

Variable (percent)	Low SGAX Firms Mean	Low SGAX Firms STD	High SGAX Firms Mean	High SGAX Firms STD
Inflation	0.19	4.43	0.03	3.88
Positive price changes	5.42	6.89	5.27	7.91
Negative price changes	−5.42	7.79	−6.25	10.48
Freq. of price changes	23.83	42.60	12.99	33.61
Freq. of positive price changes	13.67	34.35	7.33	26.06
Freq. of negative price changes	10.16	30.21	5.66	23.12
No. of goods	3,891		2,829	
Observations	203,106		141,455	
Memo: SGAX ratio	0.13	0.07	0.37	0.26

NOTE: Sample period: monthly data from 2005:M1 to 2012:M12; No. of firms = 547.

Table A-4: Liquidity, Employment, and Investment During the Financial Crisis

	Annual Data[a]						Quarterly Data[b]	
	Employment		Capital Expenditures		R&D Expenditures		Inventories	
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{LIQ}_{j,t}$	0.362***	.	1.232***	.	0.860***	.	0.058***	.
	(0.047)		(0.195)		(0.166)		(0.017)	
$\text{LIQ}_{j,t} \times \mathbf{1}[\text{CRISIS}_t = 1]$	.	0.418***	.	1.340***	.	0.851***	.	0.087***
		(0.056)		(0.256)		(0.187)		(0.028)
$\text{LIQ}_{j,t} \times \mathbf{1}[\text{CRISIS}_t = 0]$	.	0.346***	.	1.206***	.	0.862***	.	0.055***
		(0.047)		(0.197)		(0.170)		(0.027)
$\Delta \log \tilde{S}_{j,t+1}$	0.229***	0.230***	.	.	.	.	.	.
	(0.022)	(0.022)						
$\log[\Pi/K]_{j,t+1}$	.	.	0.196***	0.196***	0.089***	0.089***	.	.
			(0.029)	(0.029)	(0.030)	(0.030)		
$\log Q_{j,t}$	.	.	0.290***	0.291***	0.068	0.068	.	.
			(0.059)	(0.060)	(0.060)	(0.060)		
$\log[N/S]_{j,t}$	.	.	.	.	.	.	−0.125***	−0.126***
							(0.008)	(0.008)
$\Delta \log N_{j,t}$	.	.	.	.	.	.	0.050***	0.050***
							(0.012)	(0.012)
$\Delta \log S_{j,t}$	.	.	.	.	.	.	−0.072***	−0.072***
							(0.015)	(0.015)
$\Pr > W$[c]	.	0.075	.	0.504	.	0.927	.	0.168
R^2 (within)	0.226	0.227	0.259	0.259	0.172	0.172	0.150	0.150
No. of firms	543		553		371		571	
Observations	3,218		3,454		2,222		14,516	

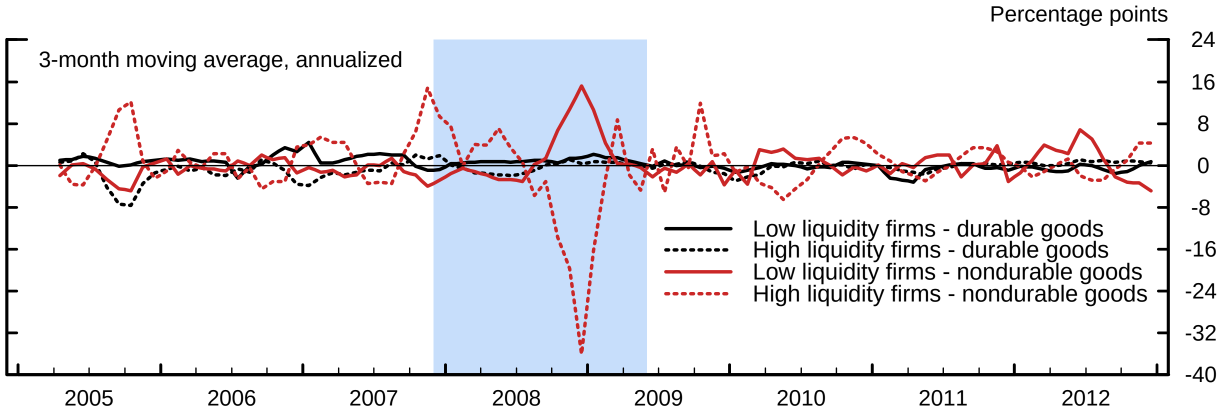
Note: The dependent variable in columns (1) and (2) is $\Delta \log E_{j,t+1}$, the log-difference in the number of employees from year t to year $t+1$; the dependent variable in columns (3) and (4) is $\log[I/K]_{j,t+1}$, the log of the ratio of capital expenditures in year $t+1$ to the stock of capital at the end of year t; the dependent variable in columns (5) and (6) is $\log[\text{RD}/K]_{j,t+1}$, the log of the ratio of R&D expenditures in year $t+1$ to the stock of capital at the end of year t; and the the dependent variable in columns (7) and (8) is $\Delta N_{j,t+1}$, the log-difference of inventories from quarter t to quarter $t+1$. In addition to the specified explanatory variables (see equations A-1–A-3 and the text for details), all specifications include firm and time fixed effects and are estimated by OLS. Asymptotic standard errors reported in parentheses are clustered at the firm level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] Sample period: 2006 to 2012 at an annual (fiscal year-end) frequency in columns (1) and (2); and 2005 to 2012 at an annual (fiscal year-end) frequency in columns (3)–(6).

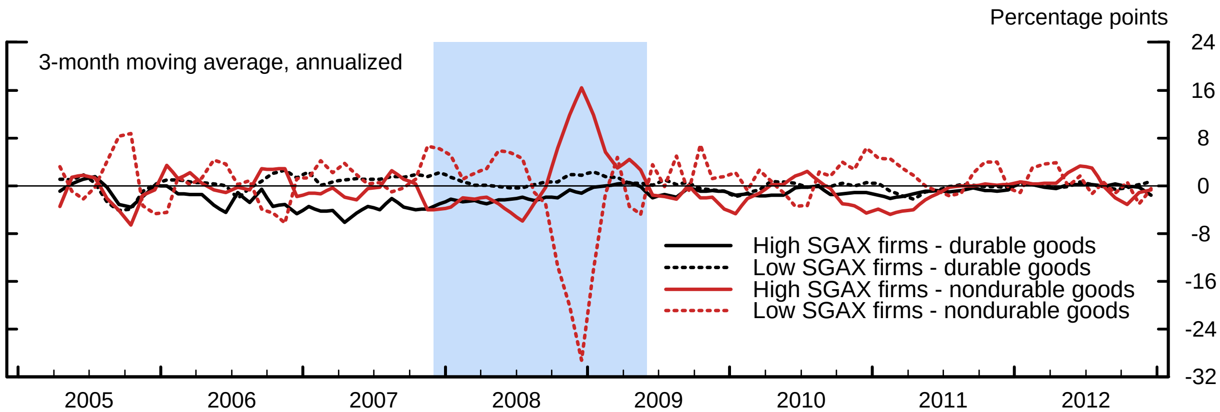
[b] Sample period: 2005:Q1 to 2012:Q4 at a quarterly frequency.

[c] p-value for the Wald test of the null hypothesis that the coefficients on the liquidity ratio ($\text{LIQ}_{j,t}$) are equal between crisis and non-crisis periods.

Figure A-1: Industry-Adjusted Producer Price Inflation
(*By Selected Firm Characteristics and Durability of Output*)



(a) By liquidity ratio and durability of output



(b) By SGAX ratio and durability of output

Note: The solid (dotted) lines in panel (a) depicts the weighted-average industry-adjusted inflation rate for low (high) liquidity firms in durable and nondurable good manufacturing industries. The solid (dotted) lines in panel (b) depicts the weighted-average industry-adjusted inflation rate for high (low) SGAX firms in durable and nondurable good manufacturing industries. All underlying series are seasonally adjusted and annualized. The shaded vertical bar represents the 2007–2009 recession as dated by the NBER.

B Model Appendix

The Model Appendix consists of three subsections. Subsection B.1 describes the model with heterogeneous firms and nominal rigidities, which is introduced in Section 5 of the main text. Subsection B.2 provides details surrounding the derivation of the log-linearized Phillips curve. And Subsection B.3 contains simulations of our benchmark model under alternative calibrations.

B.1 Model with Firm Heterogeneity and Nominal Rigidities

This section describes the key aspects of our full model—that is, the model featuring heterogeneous firms and nominal rigidities. Without loss of generality, we assume that there exist a finite number of firm types indexed by $k = 1, \ldots, N$. Firms of different types are characterized by varying degree of operating efficiency, measured by the size of the fixed operating cost. Formally, the production technology of firm i of type k is given by

$$y_{it} = \left(\frac{A_t}{a_{it}} h_{it}\right)^{\alpha} - \phi_k; \quad 0 < \alpha \leq 1, \tag{B-1}$$

where $\phi_k \geq 0$ denotes the fixed operating costs, which can take one of N-values from a set $\mathbf{\Phi} = \{\phi_1, \ldots, \phi_N\}$, with $0 \leq \phi_1 < \cdots < \phi_N$. The measure of firms of type k is denoted by Ξ_k, with $\sum_{k=1}^{N} \Xi_k = 1$. We assume that each type of firm faces the same distribution of the idiosyncratic cost shock a_{it}—that is, $\log a_{it} \overset{iid}{\sim} N(-0.5\sigma^2, \sigma^2)$, for all i and k.

The presence of quadratic adjustment costs incurred when firms change nominal prices modifies the flow-of-funds constraint as

$$0 = p_{it}c_{it} - w_t h_{it} - \frac{\gamma_p}{2}\left(\pi_t \frac{p_{it}}{p_{i,t-1}} - \bar{\pi}\right)^2 c_t - d_{it} + \varphi_t \min\{0, d_{it}\}. \tag{B-2}$$

The firm's problem of maximizing the expected present discounted value of dividends then gives rise to the following Lagrangian:

$$\begin{aligned}
\mathcal{L} = \mathbb{E}_0 \sum_{t=0}^{\infty} m_{0,t} \Bigg\{ & d_{it} + \kappa_{it}\left[\left(\frac{A_t}{a_{it}} h_{it}\right)^{\alpha} - \phi_k - c_{it}\right] \\
& + \xi_{it}\left[p_{it}c_{it} - w_t h_{it} - \frac{\gamma_p}{2}\left(\pi_t \frac{p_{it}}{p_{i,t-1}} - \bar{\pi}\right)^2 c_t - d_{it} + \varphi_t \min\{0, d_{it}\}\right] \\
& + \nu_{it}\left[\left(\frac{p_{it}}{\tilde{p}_t}\right)^{-\eta} s_{it-1}^{\theta(1-\eta)} x_t - c_{it}\right] + \lambda_{it}\left[\rho s_{i,t-1} + (1-\rho)c_{it} - s_{it}\right] \Bigg\},
\end{aligned} \tag{B-3}$$

and the associated first-order conditions for type-k firms:

$$d_{it}: \quad \xi_{it} = \begin{cases} 1 & \text{if } d_{it} \geq 0 \\ 1/(1-\varphi_t) & \text{if } d_{it} < 0; \end{cases} \tag{B-4}$$

$$h_{it}: \quad \kappa_{it} = \xi_{it} a_{it} \left(\frac{w_t}{\alpha A_t}\right) (c_{it} + \phi_k)^{\frac{1-\alpha}{\alpha}}; \tag{B-5}$$

$$c_{it}: \quad \mathbb{E}_t^a\big[\nu_{it}\big] = \mathbb{E}_t^a\big[\xi_{it}\big] p_{it} - \mathbb{E}_t^a\big[\kappa_{it}\big] + (1-\rho)\mathbb{E}_t^a\big[\lambda_{it}\big]; \tag{B-6}$$

$$s_{it}: \quad \mathbb{E}_t^a\big[\lambda_{it}\big] = \rho \mathbb{E}_t^a\big[m_{t,t+1}\lambda_{i,t+1}\big] + \theta(1-\eta)\mathbb{E}_t\left[m_{t,t+1}\mathbb{E}_{t+1}^a\big[\nu_{i,t+1}\big]\left(\frac{c_{i,t+1}}{s_{it}}\right)\right]; \tag{B-7}$$

$$\begin{aligned} p_{it}: \quad 0 = {} & \mathbb{E}_t^a\big[\xi_{it}\big] c_{it} - \eta \frac{\mathbb{E}_t^a\big[\nu_{it}\big]}{p_{it}} c_{it} - \gamma_p \frac{\pi_t}{p_{i,t-1}} \left(\pi_t \frac{p_{it}}{p_{i,t-1}} - \bar{\pi}\right) c_t \\ & + \gamma_p \mathbb{E}_t\left[m_{t,t+1}\mathbb{E}_{t+1}^a\big[\xi_{i,t+1}\big]\pi_{t+1}\frac{p_{i,t+1}}{p_{it}^2}\left(\pi_{t+1}\frac{p_{i,t+1}}{p_{it}} - \bar{\pi}\right)c_{t+1}\right]. \end{aligned} \tag{B-8}$$

The presence of heterogeneous operating costs and nominal rigidities implies that the type-specific external financing trigger is given by

$$a_t^E(\phi_k) = \frac{c_{it}}{(c_{it}+\phi_k)^{\frac{1}{\alpha}}} \frac{A_t}{w_t}\left[p_{it} - \frac{\gamma_p}{2}\left(\pi_t \frac{p_{it}}{p_{i,t-1}} - \bar{\pi}\right)^2 \frac{c_t}{c_{it}}\right], \tag{B-9}$$

which allows us to express the first-order condition governing the behavior of dividends (equation B-4) as

$$\xi_{it} = \begin{cases} 1 & \text{if } a_{it} \leq a_t^E(\phi_k) \\ 1/(1-\varphi_t) & \text{if } a_{it} > a_t^E(\phi_k). \end{cases} \tag{B-10}$$

Using equation (B-10), one can show that the expected shadow value of internal funds for firms of type k is equal to

$$\mathbb{E}_t^a\big[\xi_{it}|\phi_k\big] = \Phi(z_t^E(\phi_k)) + \frac{1}{1-\varphi_t}\big[1 - \Phi(z_t^E(\phi_k))\big] = 1 + \frac{\varphi_t}{1-\varphi_t}\big[1-\Phi(z_t^E(\phi_k))\big] \geq 1,$$

where $z_t^E(\phi_k)$ denotes the standardized value of $a_t^E(\phi_k)$. Note that $da_t^E(\phi_k)/d\phi_k < 0$, which implies that $d\mathbb{E}_t^a\big[\xi_{it}|\phi_k\big]/d\phi_k > 0$. In other words, firms with lower operating efficiency are more likely to experience a liquidity shortfall and hence face a higher expected premium on external funds.

B.1.1 Aggregation

In the presence of firm heterogeneity, the nature of the symmetric equilibrium is modified. Specifically, all firms with the same ϕ_k choose the same price level P_{kt}:

$$P_{it}^{1-\eta} = \sum_{k=1}^{N} \mathbf{1}(\phi_i = \phi_k) \times P_{kt}^{1-\eta}. \tag{B-11}$$

Aggregate inflation dynamics are then given by a weighted average of the N types of firms. Because $\pi_t \equiv P_t/P_{t-1} = 1/P_{t-1}\left(\int_0^1 P_{it}^{1-\eta} di\right)^{1/(1-\eta)}$, we can use equation (B-11) to express the aggregate inflation rate as

$$\begin{aligned}
\pi_t &= \frac{1}{P_{t-1}}\left[\int_0^1 \sum_{k=1}^{N} \mathbf{1}(\phi_i=\phi_k)\times P_{kt}^{1-\eta}di\right]^{\frac{1}{1-\eta}} \\
&= \frac{1}{P_{t-1}}\left[\sum_{k=1}^{N} P_{kt}^{1-\eta}\int_0^1 \mathbf{1}(\phi_i=\phi_k)di\right]^{\frac{1}{1-\eta}} \\
&= \left[\sum_{k=1}^{N} \Xi_k\left(\frac{P_{kt}}{P_{t-1}}\right)^{1-\eta}\right]^{\frac{1}{1-\eta}} \\
&= \left[\sum_{k=1}^{N} \Xi_k\left(\frac{P_{kt}}{P_{k,t-1}}\right)^{1-\eta}\left(\frac{P_{k,t-1}}{P_{t-1}}\right)^{1-\eta}\right]^{\frac{1}{1-\eta}}.
\end{aligned}$$

Hence, the aggregate inflation rate is determined as a weighted-average of inflation rates of heterogeneous groups:

$$\pi_t = \left[\sum_{k=1}^{N} \Xi_k p_{k,t-1}^{1-\eta}\pi_{kt}^{1-\eta}\right]^{\frac{1}{1-\eta}}, \tag{B-12}$$

where $\pi_{kt} \equiv P_{kt}/P_{k,t-1}$ is a type-specific inflation rate and $p_{kt} \equiv P_{kt}/P_t$ is a type-specific relative price. Note that the relative price p_{kt} can no longer be equalized to one in the symmetric equilibrium. The notion of a symmetric equilibrium is restricted to "within types," that is, within categories, and in equilibrium, there exists a non-degenerate distribution of relative prices.

The following Phillips curve describes the inflation dynamics of the k-type firms:

$$\begin{aligned}
0 = p_{kt}\frac{c_{kt}}{c_t} - \eta\frac{\mathbb{E}_t^a\left[\nu_{kit}|\phi_k\right]}{\mathbb{E}_t^a\left[\xi_{kit}|\phi_k\right]}\frac{c_{kt}}{c_t} - \gamma_p\pi_{kt}\pi_t\left(\pi_{kt}\pi_t-\bar{\pi}\right) \\
+\gamma_p\mathbb{E}_t\left[m_{t,t+1}\frac{\mathbb{E}_{t+1}^a\left[\xi_{ki,t+1}|\phi_k\right]}{\mathbb{E}_t^a\left[\xi_{kit}|\phi_k\right]}\pi_{k,t+1}\pi_{t+1}\left(\pi_{k,t+1}\pi_{t+1}-\bar{\pi}\right)\frac{c_{t+1}}{c_t}\right].
\end{aligned} \tag{B-13}$$

The same notion of the modified symmetric equilibrium can be applied to equilibrium output:

$$c_{it}^j = \sum_{k=1}^{N}\mathbf{1}(\phi_i=\phi_k)\times c_{kt}^j.$$

Because the household sector is still characterized by a symmetric equilibrium, we can drop the "j" superscript. The individual demand for products produced by firms with efficiency rank k is then given by

$$c_{kt} = \left(\frac{p_{kt}}{\tilde{p}_t}\right)^{-\eta} s_{k,t-1}^{\theta(1-\eta)}x_t, \tag{B-14}$$

where

$$\tilde{p}_t = \left[\sum_{k=1}^{N}\Xi_k p_{kt}^{1-\eta}s_{k,t-1}^{\theta(1-\eta)}\right]^{\frac{1}{1-\eta}}; \tag{B-15}$$

and

$$x_t = \left[\sum_{k=1}^{N}\Xi_k\left(\frac{c_{kt}}{s_{k,t-1}^{\theta}}\right)^{1-\frac{1}{\eta}}\right]^{\frac{1}{1-\frac{1}{\eta}}}. \tag{B-16}$$

Aggregate demand should then satisfy

$$c_t = \left[\sum_{k=1}^{N} \Xi_k \left[\exp(0.5\alpha(1+\alpha)\sigma^2) h_{kt}^{\alpha} - \phi_k \right]^{1-\frac{1}{\eta}} \right]^{\frac{1}{1-\frac{1}{\eta}}}, \tag{B-17}$$

while the type-specific conditional labor demand satisfies

$$h_{kt} = \left[\frac{c_{kt} + \phi_k}{\exp(0.5\alpha(1+\alpha)\sigma^2)} \right]^{\frac{1}{\alpha}}, \tag{B-18}$$

with $h_t = \sum_{k=1}^{N} h_{kt}$. (The term $\exp(0.5\alpha(1+\alpha)\sigma^2)$ is the expected value of $1/a_{it}$, which is strictly greater than one due to Jensen's inequality.)

B.1.2 Equilibrium Relative Prices in the Steady State

In the steady state, the Phillips curve (equation B-13) implies

$$p_k = \eta \frac{\mathbb{E}^a [\nu_i | \phi_k]}{\mathbb{E}^a [\xi_i | \phi_k]}. \tag{B-19}$$

From the first-order conditions for the habit stock (equation B-7), we have

$$\frac{\mathbb{E}^a [\lambda_i | \phi_k]}{\mathbb{E}^a [\xi_i | \phi_k]} = \frac{\theta(1-\eta)\beta}{1-\rho\beta} \frac{\mathbb{E}^a [\nu_i | \phi_k]}{\mathbb{E}^a [\xi_i | \phi_k]}. \tag{B-20}$$

Combining equations (B-19) and (B-20) yields

$$\frac{\mathbb{E}^a [\lambda_i | \phi_k]}{\mathbb{E}^a [\xi_i | \phi_k]} = p_k \frac{\theta(1-\eta)\beta}{\eta(1-\rho\beta)}. \tag{B-21}$$

In the steady state, the first-order conditions for labor input (equation B-5) and production scale (equation B-6) together imply

$$\frac{\mathbb{E}^a [\nu_i | \phi_k]}{\mathbb{E}^a [\xi_i | \phi_k]} = -\frac{\mathbb{E}^a [\xi_i a_i | \phi_k]}{\mathbb{E}^a [\xi_i | \phi_k]} \frac{w}{\alpha A} (c_k + \phi_k)^{\frac{1-\alpha}{\alpha}} + p_k + (1-\rho) \frac{\mathbb{E}^a [\lambda_i | \phi_k]}{\mathbb{E}^a [\xi_i | \phi_k]}. \tag{B-22}$$

Substituting equations (B-19) and (B-21) into equation (B-22) yields

$$p_k = \frac{\eta(1-\rho\beta)}{(\eta-1)[(1-\rho\beta) - \theta\beta(1-\rho)]} \frac{\mathbb{E}^a [\xi_i a_i | \phi_k]}{\mathbb{E}^a [\xi_i | \phi_k]} \frac{w}{\alpha A} (c_k + \phi_k)^{\frac{1-\alpha}{\alpha}}. \tag{B-23}$$

The type-specific external financing triggers in the steady state are given by

$$a_k^E = \frac{p_k c_k}{(c_k + \phi_k)^{\frac{1}{\alpha}}} \frac{A}{w}, \tag{B-24}$$

while the consumption aggregators imply

$$\frac{c_k}{c_l} = \left(\frac{p_k}{p_l} \right)^{-\eta} \frac{s_k^{\theta(1-\eta)}}{s_l^{\theta(1-\eta)}}; \quad k \neq l, \tag{B-25}$$

and

$$x = \left[\sum_{k=1}^{N} \Xi_k \left(c_k^{1-\theta} \right)^{1-\frac{1}{\eta}} \right]^{\frac{1}{1-\frac{1}{\eta}}}. \tag{B-26}$$

General equilibrium consistency conditions require

$$1 = \left[\sum_{k=1}^{N} \Xi_k p_k^{1-\eta} \right]^{\frac{1}{1-\eta}}, \tag{B-27}$$

which is the steady-state version of equation (B-12), with $\pi = \pi_k = 1$.

The household j's preferences over the habit-adjusted consumption bundle x_t^j and labor h_t^j are given by the following (CRRA) utility function:

$$U(x_t^j, h_t^j) = \frac{x_t^{1-\theta_x}}{1-\theta_x} - \frac{\zeta}{1+\theta_h} h_t^{1+\theta_h}.$$

The resulting market-clearing conditions associated with the labor and goods markets imply

$$\frac{w}{\tilde{p}} x^{-\theta_x} = \zeta h^{\theta_h}, \tag{B-28}$$

and

$$c = \left[\sum_{k=1}^{N} \Xi_k \left[\exp(0.5\alpha(1+\alpha)\sigma^2) h_k^{\alpha} - \phi_k \right]^{1-\frac{1}{\eta}} \right]^{\frac{1}{1-\frac{1}{\eta}}}, \tag{B-29}$$

respectively, where the type-specific conditional labor demand satisfies

$$h_k = \left[\frac{c_k + \phi_k}{\exp(0.5\alpha(1+\alpha)\sigma^2)} \right]^{\frac{1}{\alpha}}, \tag{B-30}$$

with

$$h = \sum_{k=1}^{N} h_k. \tag{B-31}$$

In the steady state, the deep-habit adjusted price index is given by

$$\tilde{p} = \left[\sum_{k=1}^{N} \Xi_k p_k^{1-\eta} c_k^{\theta(1-\eta)} \right]^{\frac{1}{1-\eta}}, \tag{B-32}$$

which is the steady-state version of equation (B-15). The system of equations (B-23)–(B-32) can then be solved numerically for $4N + 5$ variables: p_k, c_k, a_k^E, and h_k, $k = 1, \ldots, N$; and x, w, $\tilde{p}$, h, and c.

B.2 The Log-Linearized Phillips Curve

To derive the log-linearized Phillips curve (equation 26 in the main text), we use the first-order condition with respect to p_{it} (equation B-8), impose the symmetric equilibrium conditions (that is, $p_{it} = 1$ and $c_{it} = c_t$), and log-linearize the resulting expression to obtain

$$\hat{\pi}_t = -\frac{1}{\gamma_p}(\hat{\nu}_t - \hat{\xi}_t) + \beta \mathbb{E}_t \big[\hat{\pi}_{t+1} \big], \tag{B-33}$$

where $\hat{x}_t$ denotes the log-deviation of a generic variable x_t from its deterministic steady-state value of $\bar{x}$. In equation (B-33), the term $\hat{\nu}_t - \hat{\xi}_t$ is the log-deviation of the ratio $\mathbb{E}_t^a\left[\nu_{it}\right]/\mathbb{E}_t^a\left[\xi_{it}\right]$, which measures the value of internal funds relative to that of marginal sales:

$$\frac{\mathbb{E}_t^a\left[\nu_{it}\right]}{\mathbb{E}_t^a\left[\xi_{it}\right]} = 1 - \frac{\mathbb{E}_t^a\left[\kappa_{it}\right]}{\mathbb{E}_t^a\left[\xi_{it}\right]} + (1-\rho)\frac{\mathbb{E}_t^a\left[\lambda_{it}\right]}{\mathbb{E}_t^a\left[\xi_{it}\right]}. \tag{B-34}$$

Using the first-order condition with respect to h_{it} (equation B-5), one can show that the first two terms on the right-hand side of equation (B-34) are equivalent to $(\tilde{\mu}_t - 1)/\tilde{\mu}_t$, where $\tilde{\mu}_t \equiv \mu_t\mathbb{E}_t^a\left[\xi_{it}\right]/\mathbb{E}_t^a\left[\xi_{it}a_{it}\right]$ is the financially adjusted markup. By iterating the first-order condition with respect to the habit stock s_{it} forward, the closed-form solution for the last term in equation (B-34) is given by

$$\frac{\mathbb{E}_t^a\left[\lambda_{it}\right]}{\mathbb{E}_t^a\left[\xi_{it}\right]} = \theta(1-\eta)\mathbb{E}_t\left[\sum_{s=t}^{\infty}\tilde{\beta}_{t,s+1}\frac{\mathbb{E}_s^a\left[\xi_{i,s+1}\right]}{\mathbb{E}_t^a\left[\xi_{it}\right]}\left(\frac{\tilde{\mu}_{s+1}-1}{\tilde{\mu}_{s+1}}\right)\right], \tag{B-35}$$

where

$$\tilde{\beta}_{t,s+1} \equiv m_{s,s+1}g_{s+1} \times \prod_{j=1}^{s-t}\left[\rho + \theta(1-\eta)(1-\rho)g_{t+j}\right]m_{t+j-1,t+j}$$

denotes the growth-adjusted discount factor and $g_t \equiv c_t/s_{t-1} = (s_t/s_{t-1} - \rho)/(1-\rho)$.

To obtain the term $\hat{\nu}_t - \hat{\xi}_t$ in equation (B-33), we substitute equation (B-35) into equation (B-34) and log-linearize the right-hand side of the resulting expression. The log-linearized Phillips curve can then be expressed as

$$\begin{aligned}\hat{\pi}_t \quad = \quad & -\frac{\omega(\eta-1)}{\gamma}\left[\hat{\mu}_t + \mathbb{E}_t\sum_{s=t}^{\infty}\chi\tilde{\delta}^{s-t+1}\hat{\mu}_{s+1}\right] + \beta\mathbb{E}_t\left[\hat{\pi}_{t+1}\right] \\ & + \frac{1}{\gamma}\left[\eta - \omega(\eta-1)\right]\mathbb{E}_t\sum_{s=t}^{\infty}\chi\tilde{\delta}^{s-t+1}\left[(\hat{\xi}_t - \hat{\xi}_{s+1}) - \hat{\beta}_{t,s+1}\right],\end{aligned}$$

where $\omega = 1 - \beta\theta(1-\rho)/(1-\rho\beta)$ and $\tilde{\delta} = \beta[\rho + \theta(1-\eta)(1-\rho)]$.

B.3 Alternative Calibrations

This section conducts a sensitivity analysis of the model's main results with respect to alternative calibrations. First, we consider the sensitivity of the results reported in the main text to alternative values of the following key parameters: (1) the elasticity of labor supply (θ_h); (2) the elasticity of substitution between differentiated goods (η); and (3) the strength of deep habits (θ). As noted in the main text, our benchmark values for these parameters are $\theta_h = 5$, $\eta = 2$, and $\theta = -0.80$. As an alternative, we consider three different calibrations: (1) lower labor supply elasticity: $\theta_h = 2$; (2) higher elasticity of substitution between differentiated goods: $\eta = 4$, and (3) less powerful deep-habit mechanism: $\theta = -0.40$. In each of the three alternatives, the remaining model parameters are fixed at their benchmark values.

Figure B-1 shows the dynamics of output and inflation under these alternative calibrations in response to a financial shock, a disturbance that temporarily boosts the cost of external finance. For comparison purposes, the solid lines depict the corresponding responses from the baseline model (see Figure 7 in the main text). Imposing a significantly less elastic labor supply and a considerably greater degree of substitution across goods leads to responses that are qualitatively and quantitatively very similar to those implied by our baseline calibration. In contrast, halving the strength of the deep-habit mechanism does attenuate the response of both output and inflation to financial shocks. The latter finding should not be at all surprising given that the main propagation mechanism emphasized in our paper involves the interaction of customer markets and financial market frictions. Nevertheless, this calibration fully preserves the main conclusion of our model—namely, that a temporary deterioration in the firms' internal liquidity positions reduces the financial capacity of the economy and directly shifts the Phillips curve upward.

To see how γ_p, the parameter governing the degree of price stickiness in our model, maps to a Calvo-style price setting, consider a standard New Keynesian Phillips curve (Woodford, 2003), which relates current inflation π_t to expected future inflation and a measure of aggregate marginal costs mc_t, according to

$$\pi_t = \beta E_t \pi_{t+1} + \lambda mc_t + u_t,$$

where $0 < \beta < 1$ is the discount factor, the parameter λ is a function of the structural parameters, and u_t is a random disturbance interpreted as a shock to firms' markups. Specifically, in this setup, $\lambda = (1-\gamma_c)(1-\beta\gamma_c)/\gamma_c$, where $0 < 1-\gamma_c < 1$ is the fraction of firms that are allowed to optimally reset prices in each period.

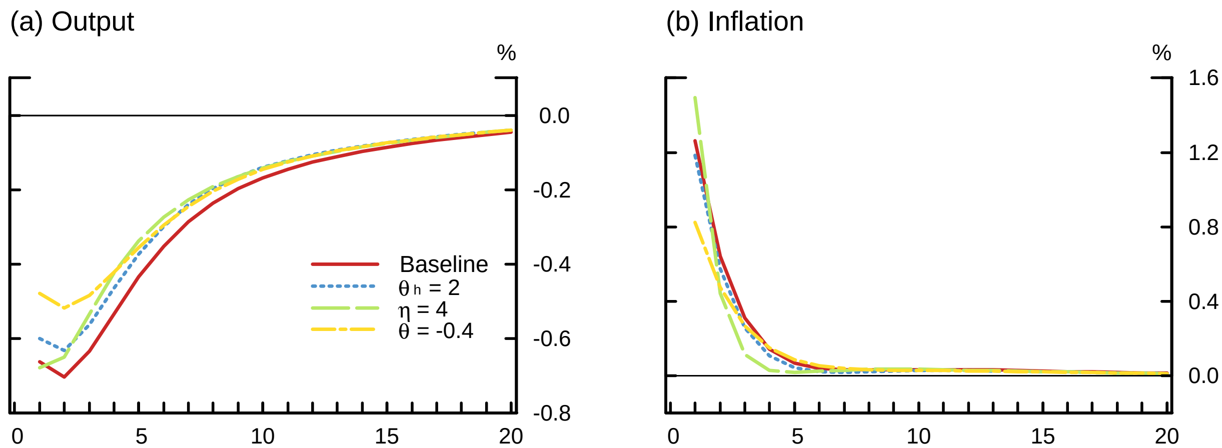
The above Phillips curve can also be derived under the assumption of quadratic adjustment costs for nominal prices (Rotemberg, 1982), in which case $\lambda = (\eta - 1)/\gamma_p$, where η is the elasticity of substitution within the Dixit-Stiglitz aggregator and γ_p is the parameter in the quadratic adjustment cost function. Our baseline calibration of $\eta = 2$ and $\gamma_p = 10$ thus implies that $\lambda = 0.1$. With β close to 1, solving $(1-\gamma_c)^2/\gamma_c = 0.1$ implies that $\gamma_c = 0.73$ or $\gamma_c = 1.37$. By assumption $0 < 1-\gamma_c < 1$, so our calibration of $\gamma_p = 10$ implies that $1-\gamma_c = 0.27$, or that about 27 percent of firms reset their prices in each quarter.

To show how differences in the degree of price stickiness affect the model dynamics in cases where the economy is perturbed by a financial shock, Figure B-2 shows the responses of output and inflation under two alternative values of γ_p. Again, for comparison purposes, the solid lines depict the corresponding responses from the baseline model with $\gamma_p = 10$ (see Figure 7 in the main text). According to these simulations, doubling the degree of nominal price rigidities ($\gamma_p = 20$) dampens the response of both output and inflation to financial shocks; conversely, halving the degree of price stickiness ($\gamma_p = 5$) implies a more pronounced reaction of both macroeconomic aggregates to such disturbances.

The economics underlying these differences are clear. Because of frictions in financial markets, firms would like to increase prices in response to the adverse financial shock in order to preserve internal liquidity. When prices are more rigid, however, firms find it more costly to raise prices. As a result, the markup increases by less, and the response of output is significantly attenuated, relative to a model with more flexible prices. These dynamics stand in stark contrast to those implied by the typical New Keynesian models, in which an increased degree of nominal price stickiness leads to a more volatile output.[36] It is worth noting that these results apply only to changes in the degree of price stickiness—an increase in nominal wage rigidities makes the firms' cost structure less flexible and hence amplifies the financial mechanism in our model.

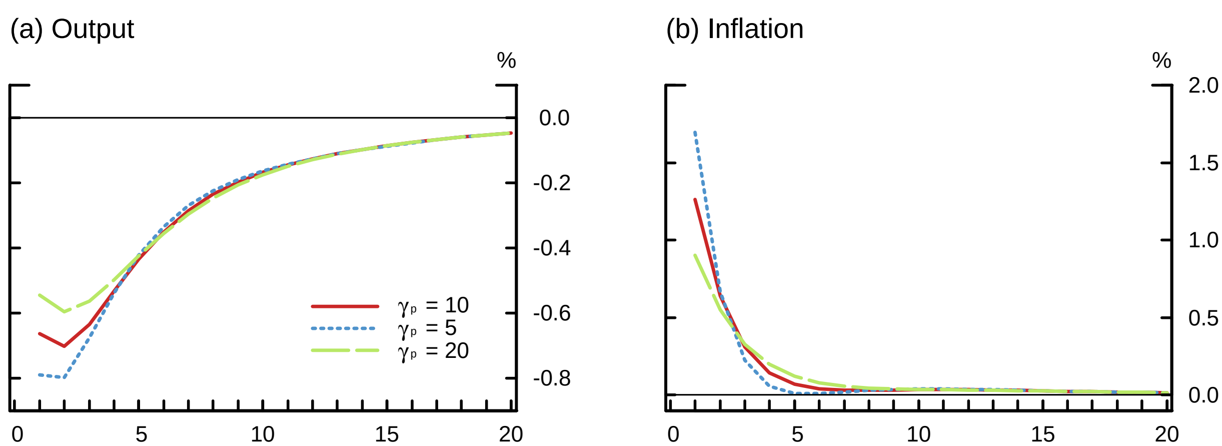
[36] Increased price flexibility, however, can be stabilizing in cases where monetary policy does not respond strongly to inflation, a special case of which is the zero lower bound (Bhattarai et al., 2014).

Figure B-1: Financial Shock
(*Alternative Calibrations*)



Note: Panel (a) of the figure depicts the model-implied responses of output to a temporary increase in the time-varying equity dilution cost parameter φ_t, while panel (b) depicts the corresponding responses of inflation. All responses are based on models featuring nominal rigidities and financial frictions, with the level of financial frictions calibrated to a non-crisis situation ($\bar{\varphi} = 0.3$); see the main text for details.

Figure B-2: Financial Shock
(*The Role of Nominal Rigidities*)



Note: Panel (a) of the figure depicts the model-implied responses of output to a temporary increase in the time-varying equity dilution cost parameter φ_t, while panel (b) depicts the corresponding responses of inflation. All responses are based on models featuring financial frictions, with the level of financial frictions calibrated to a non-crisis situation ($\bar{\varphi} = 0.3$); see the main text for details.